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Climate change

Quantifying the health impact at national and local levels

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Preface

The disease burden of a population, and how that burden is distributed, are important pieces of information for prioritizing and defining strategies to protect population health. For policy-makers, disease burden estimates provide an indication of the current and future health gains that could be achieved by targeted protection from specific risks. To help provide a reliable source of information for policy-makers, WHO has developed methods to analyse the impacts of risks for health, and has estimated the impacts of 26 risk factors worldwide, including climate change (WHO, 2002; McMichael et al., 2004).

The Environmental Burden of Disease (EBD) series aims at supporting countries to generate reliable information for policy-making, by presenting methods for estimating the environmental burden at national and regional levels. The introductory volume in the series outlines the general method (Prüss-Üstün et al., 2003), while subsequent volumes address specific environmental risk factors. The guides on specific risk factors are organized similarly, first outlining the evidence linking the risk factor to health, and then describing a method for estimating the health impact of that risk factor on the population. All the guides take a practical, step-by-step approach and use numerical examples. The methods described can be adapted both to regional and national levels, and can be tailored to suit data availability.

It has been shown that climate change causes impacts on various communicable and non-communicable diseases and injuries (WHO, 2002; McMichael et al., 2003a; Ezzati et al., 2004). While the environmental risk is distributed globally, most of the actions that are necessary to protect health under a changing climate are local. Quantitative assessment of the size and distribution of health risks can therefore be an important tool in identifying which actions will be most effective in adapting to climate change. They may also provide an incentive to cooperate at the international level to reduce our impacts on the global climate.

Climate change is unusual in its global scope, its irreversibility (over human timescales), and the very wide range of threats that it poses to health and other aspects of human well-being. While methods for describing and measuring health effects are still at an early stage of development and many uncertainties remain, it is important to provide a framework and first set of guidance for assessing health impacts, so that societies are better equipped to address this emerging threat.

Affiliations and acknowledgements

Diarmid Campbell-Lendrum, Annette Prüss-Üstün and Carlos Corvalán are from the World Health Organization, and Rosalie Woodruff is from the Australian National University.

In preparing this document, we drew on the methods developed for estimating the burden of disease caused by climate change at the global level, and with Australasia. We therefore thank the additional co-authors in these analyses, particularly Tony McMichael of the Australian National University, who led both assessments.

We also thank the US Environmental Protection Agency for having supported the development of the Environmental Burden of Disease approaches.

Glossary and abbreviations

CIESIN	Center for International Earth Science Information Network, Columbia University, USA
CRU	Climatic Research Unit, University of East Anglia, UK
CSIRO	Commonwealth Scientific and Industrial Research Organization, Australia
DALYs	Disability-Adjusted Life Years
EM-DAT	Emergency Disasters Database
ENSO	El Niño Southern Oscillation
IFRC	International Federation of the Red Cross and Red Crescent
IPCC	Intergovernmental Panel on Climate Change
OFDA/CRED	Office of US Foreign Disaster Assistance/ Centre for Research on the Epidemiology of Disasters
GIS	Geographic Information System
GDP	Gross Domestic Product
GHGs	Greenhouse Gases
GNP	Gross National Product
MARA	Mapping Malaria Risk in Africa Project
NASA	North American Space Administration
PM_{10}	Particulate matter, 10 microns - a measure of particulate air pollution
SRES	Special Report on Emissions Scenarios
UNDMT	United Nations Disaster Management Training Program
WHO	World Health Organization
WHO/PTC	World Health Organization Pan-African Training Centre

Summary

Climate change is an emerging risk factor for human health. There is now widespread consensus among the scientific community that the earth is warming, that this is mainly due to human activities, and that this will continue for at least the next several decades (IPCC, 2001b; Oreskes, 2004). It is also clear that weather and climate exert a major influence on human health, both through direct effects of extreme events such as heatwaves, floods and storms, and more indirect influences on the distribution and transmission intensity of infectious diseases, and on the availability of freshwater and food.

It is therefore important to obtain the best possible assessment of the likely health impacts of climate change. This is a particularly challenging task. Compared to other environmental risk factors, climate range is a newly recognized phenomenon, with global scope, operating over long time periods and affecting an unusually wide range of health outcomes. The guidance presented here therefore outlines a general approach, and describes how the methods that were applied in the World Health Organization global comparative risk assessment project, and a regional assessment in Australasia, can be "down-scaled" to the national or sub-national level. It also highlights where further research is likely to improve the assessment. It should therefore be useful in generating preliminary estimates of some of the health effects of climate change, and as a guide to developing more comprehensive and accurate assessment in the future.

The general approach consists of; (i) Selecting an appropriate set of scenarios of alternative possible futures (e.g. lower or higher rates of emissions of greenhouse gases, population growth etc.), and the timescale over which to carry out the assessment; (ii) Mapping the corresponding projected changes in climate properties; (iii) Identifying the range of health outcomes that are both climate-sensitive and important in public health terms within the assessment population; (iv) Quantifying the relationship between climate and each health outcome; (v) Linking the exposure measurement to the climate-health model; and (vi) using this information to calculate the climate change attributable burden of specific diseases.

Subsequent sections describe assessment methods that were used in the previous global and regional assessments, for a range of climate-sensitive health outcomes. These are deaths in thermal extremes, deaths in coastal and inland floods, and disease burdens from malaria and diarrhoea. A detailed step-by-step example is given for the Australasian assessment.

Estimates of the health impacts from climate change have two main uses in policy-making. Firstly, they provide a fuller picture of the consequences of mitigating, or failing to mitigate, emissions of greenhouse gases that are the main anthropogenic contribution to climate change. Secondly, they can help to identify which populations are likely to suffer the greatest impacts of climate change, and from which specific diseases. They can therefore help inform policies and allocate resources to adapt to climate change.

1. Introduction to the risk factor

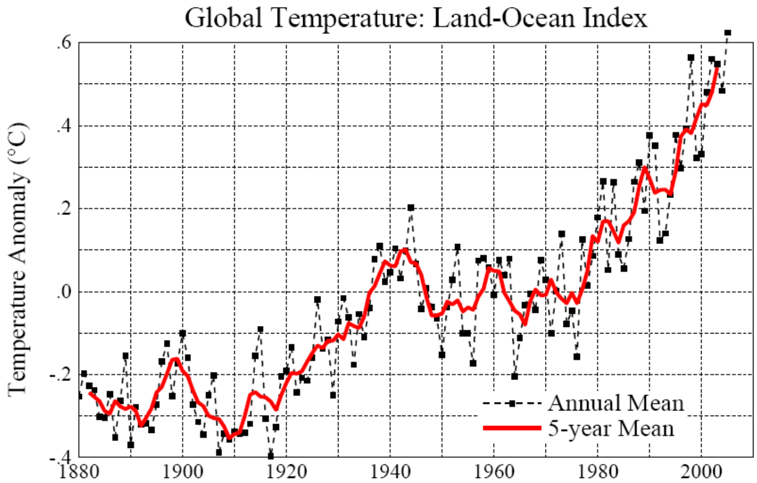
Climate is always changing, on daily, seasonal and inter-annual time scales. In addition to this natural climate variability there is abundant evidence that average climatic conditions measured over long time periods (conventionally decades or longer) are changing and at an unprecendented rate (Box 1). Numerous climatological research groups have investigated the possible causes and effects of these changes. In order to provide a consensus of leading scientific opinion, the United Nations established the Intergovernmental Panel on Climate Change (IPCC) to review and summarise evidence on the causes of the observed climatic changes, on the likely extent of future changes, and the associated impacts on human societies and natural systems.

Box 1: Terms in this chapter

Climate change means human-induced (anthropogenic) change to the global climate system. These changes are expressed differently at regional areas across the planet. For example, northern high latitude regions are warming faster than elsewhere, and rainfall is expected to decrease (relative to baseline conditions) in some areas and increase in others. Natural climate variability means fluctuations in climate patterns (at global, regional or local levels) that are within the bounds of expected probability, based on the observed record of climate taken from the instrumental record or derived from tree rings, coral, cave deposits, etc. “Health outcomes” are all the possible results that may stem from exposure to, in this instance, climate change (Last, 2001) . These include disease, death and injury. Regional refers to a group of countries (e.g. Western Europe, the Pacific) and local refers to sub-national areas (such as southern Thailand, Western Australia).

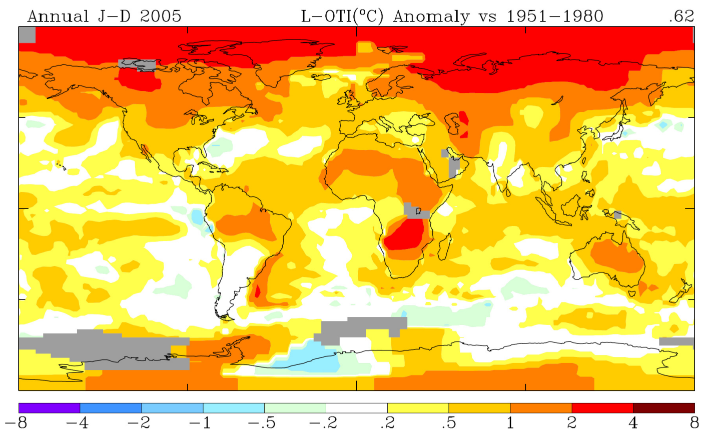
In its 2001 report, the IPCC estimated that the global average land and sea surface temperature has increased by 0.6°C (±0.2) since the mid-19th century, with most change occurring since 1976 (Fig.1a to 1c). This increase is outside the limits of natural climate variability recorded over the past 1000 years (Crowley, 2000). Patterns of precipitation have also changed: arid and semi-arid regions appear to be becoming drier. Other areas, especially those in mid-to-high latitudes, are becoming generally wetter, and at the same time there is an increasing frequency in extreme rainfall events (Karl and Knight, 1998; Mason et al., 1999). The causes of these changes are also increasingly well understood. The IPCC reviewed model simulations of the effect of greenhouse gas (GHG) emissions on past observed climate variations, and evaluated the influence of natural phenomena such as solar and volcanic activity. They concluded that natural phenomena alone are insufficient to explain recent trends, and that "*there is new and stronger evidence that most of the warming observed over the last 50 years is likely to be attributable to human activities*" (IPCC, 1996; IPCC, 2001b).

Figure 1a Past climate - Line plot of global mean land-ocean temperature index *1880 to present, relative to 1951-1980 conditions*



Source: (NASA, 2006)

Figure 1b Present climate: Map of the mean temperature throughout the year in 2005, relative to average conditions for the period 1951-1980.



Based on data from (NASA, 2006).

Figure 1c Future climate: Projected future changes in global mean temperature over the next Century
Based on a range of projections of greenhouse gas emissions, applied to multiple climate models

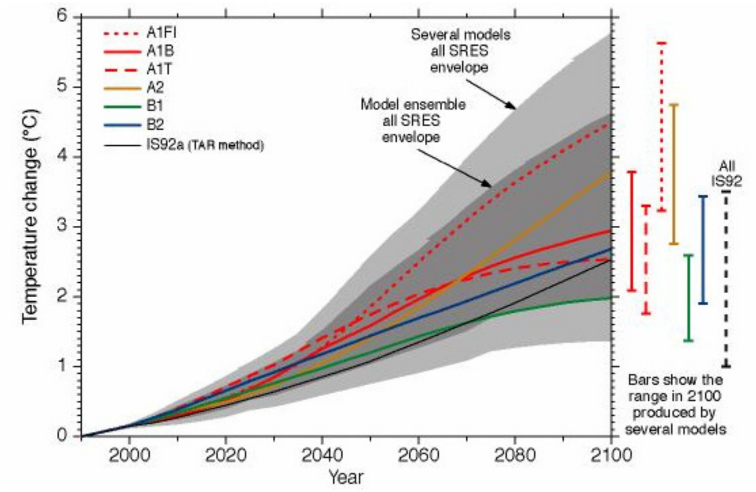


Figure from (IPCC, 2001b)

Climatologists have been able to simulate the effects of past, present and future GHG emissions on future climate. Based on a range of social development scenarios and model parameterizations, and if no specific actions were taken to reduce greenhouse gas emissions, global temperatures would rise between 1.4 to 5.8°C from 1990 to 2100 (IPCC, 1996; IPCC, 2001b). The projections for precipitation and wind speed are less consistent in terms of the magnitude of change, but there is agreement that significant changes will occur in mean conditions and the frequency and intensity of extreme events (Table 1).

Climate influences human populations directly, through the effects of ambient temperature on human physiology (leading to heat stress or heat stroke), and the deaths and injuries caused by extreme weather events (floods, fires, hurricanes etc). There are also indirect effects. The patterns of many vector-borne and other infectious diseases are known to vary seasonally and inter-annually in response to changes in weather. Agricultural production can decrease due to drought or storm damage, leading to malnutrition, famine, and population displacement.

The anthropogenic climate change that has occurred so far, although small in comparison to that projected for the coming century, has already had demonstrable effects on a wide variety of ecosystems (Walther et al., 2002). It is therefore highly probable that anthropogenic climate change will have some effect on human health. At best it will take decades (most likely centuries), and significant economic and societal changes, to stabilise the changes to the climate system that are already in train. It is therefore essential to have estimates of the likely magnitude of health effects to inform decisions about reducing greenhouse gas emissions (and hence the rate and extent of global warming), and to develop strategies for those changes that are already inevitable. Given the complex linkages between climate change and health, attempts to estimate the health impacts of climate change should be based on careful analysis, and acknowledge the inherent uncertainty of any future projections.

Table 1 Estimates of confidence[a] in observed and projected changes in extreme weather and climate events

Changes in phenomenon	Confidence in observed changes (latter half of 1900s)[a]	Confidence in projected changes (during the 21st century)[a]
Higher maximum temperatures and more hot days over nearly all land areas	Likely	Very likely
Higher minimum temperatures, fewer cold days and frost days over nearly all land areas	Very likely	Very likely
Reduced diurnal temperature range over most land areas	Very likely	Very likely
Increase of heat index[b] over land areas	Likely, over many areas	Very likely, over most areas
More intense precipitation events[c]	Likely, over many Northern Hemisphere mid- to high latitude land areas	Very likely, over many areas
Increased summer continental drying and associated risk of drought	Likely, in a few areas	Likely, over most mid-latitude continental interiors. (Lack of consistent projections in other areas)
Increase in tropical cyclone peak wind intensities[d]	Not observed in the few analyses available	Likely, over some areas
Increase in tropical cyclone mean and peak precipitation intensities[d]	Insufficient data for assessment	Likely, over some areas

a) Judgement estimates for confidence: *virtually certain* (greater than 99% chance that the result is true); *very likely* (90-99% chance); *likely* (66-90% chance); *medium likelihood* (33-66% chance); *unlikely* (10-33% chance); *very unlikely* (1-10% chance); *exceptionally unlikely* (less than 1% chance).
b) Based on warm season temperature and humidity
c) For other areas, there are either insufficient data or conflicting analyses.
d) Past and future changes in tropical cyclone location and frequency are uncertain.
Adapted from (IPCC, 2001b)

1.1 Quantifying health impacts from climate change

In quantifying health impacts from environmental risks we are attempting to answer the following questions:

1. How much disease is caused by a particular risk factor (the attributable burden of disease)?
2. How much could be avoided by making plausible reductions in the risk factor (the avoidable burden of disease)?

For most other risk factors, these burdens are reached by estimating the ratio of the risk of disease in the exposed population to the risk among people not exposed (the 'unexposed'). The associated relative risk (incidence or prevalence of disease) is combined with the proportion of the population exposed, to measure the impact fraction of the particular exposure.

This standard approach cannot be directly applied to the situation of climate change. First, all populations are exposed to different aspects of the same climate system, rather than a defined proportion of the population being exposed to the risk factor (e.g. the proportion of the population who are smokers). Second, anthropogenic climate change is a gradual process, occurring over many decades, against a background of natural climate variability and changes in other factors that determine human health. Although it is possible to monitor the effects of gradual climate change on some limited health indicators in specific sites (Wilkinson et al., 2003), it is not possible to extrapolate these to all health effects of climate change across the entire global population. Finally, the very long persistence of GHGs in the atmosphere makes climate change an unusual environmental exposure. In this context it is less important to measure current impacts (the result of past GHG emissions that cannot be altered) and more important to estimate future impacts (which could still be avoided by policy decisions in the near future).

The most complete estimation of the health effects of climate change will come from

- measuring the effects of climate variation (and other influences) on health in the present and recent past, and
- applying these derived relationships to projections of likely changes in climatic conditions in the future (i.e. the results of climatological models).

This allows the calculation of attributable and avoidable burdens by comparing predicted disease rates if (1) no ameliorative action is taken, so that climate change continues along its current trajectory, (2) action is taken to reduce climate change to some plausible level, or (3) climate had remained unaffected by human activities (the 'counterfactual' situation: conservatively approximated by taking average conditions from a period before the climate had been strongly affected by human activites - e.g. 1961-1990). The attributable burden is determined by comparing the estimated disease burdens under unmitigated climate change (i.e. 1) to those under an "unchanged" climate (i.e. 3). The avoidable burden is determined by comparing disease rates associated with unmitigated climate change with those under climate change reduction scenarios (i.e. 2).

1.2 Why assess global climate change impacts at the national level?

The WHO comparitive risk assessment exercise has generated estimates of climate change health impacts at the global level and for each of the 14 WHO regions (WHO, 2002; McMichael et al., 2003a; Ezzati et al., 2004). These estimates provide a broad overview of the likely scale of impacts, but the aggregated results for the WHO regions are of limited relevance for policy at the national level.

Although climate change is a global exposure, there are several reasons why geographical variation in impacts is expected. First, the predicted rate of change in different climate properties varies in different regions of the world (Figure 1b, Table 1). Second, populations differ in their vulnerability to changes in climate. Some regions have baseline conditions that already threaten health. For example, an increase in the frequency of high temperatures may be more hazardous in tropical New Delhi than in temperate London. Third, the capacity of populations to respond to change also varies. Public health systems in western Europe or Australia would have a greater capacity to absorb increases in transmission of mosquito-borne pathogens than most African countries. Within countries, certain sub-populations will be more vulnerable to changing climate exposures (such as those living in flood-prone areas).

There is a particular advantage in carrying out national assessments that:

- use high-resolution future climate projections
- take account of climate-sensitive health impacts that are important locally (rather than globally)
- use the statistical relationships between climate and health outcomes that are relevant for the country
- can identify sub-populations that would suffer disproportionately, due to a lower capacity to adapt to changing conditions.

1.3 Selecting spatial boundaries for a study

The boundaries of an area to be assessed within a country are often determined by the information required for policy development. Climate change health policies often want to: (1) estimate the total health impact of climate change across the population (to underscore the importance of addressing the issue of climate change as a whole), or (2) estimate the size of specific health effects in particular vulnerable populations (to enable identification of communities where targeted adaptation strategies should be developed).

To address the first policy need, it is appropriate to include the total population of the country in the analysis. The assessment will still need to account for intra-population variability in the exposure, such as applying the effect of sea-level rise only to coastal populations. However, it should be possible to combine the various effects to give an approximation of the aggregate impact across, for example, a whole country. The first category approach is exemplified by the global burden of disease assessment, where impacts were first estimated for each of the 14 WHO sub regions, taking into account differences in vulnerability due to baseline climate, economic development, and pre-existing disease rates. Then these results were aggregated across diseases and sub regions to give a global estimate of disease burden (WHO, 2002; McMichael et al., 2004). This approach has the advantage of being comprehensive, but the disadvantage of increasing uncertainty by extrapolating throughout populations. It also obscures effects on particularly vulnerable populations.

The second policy need may be better addressed through pre-selecting study populations based on *a priori* information on vulnerability and considerations of how public health protection measures could be implemented. For example, it is well established that the effects of heat waves are more severe for older people (due to changes in physiology) who live in urban settlements (due to the urban heat-island effect) (WHO, 2004a). Also, decisions that affect population vulnerability to heat stress – such as developing heat-watch warning systems in the short term or urban planning in the long term – are usually made at the sub national (city or municipality) rather than national level. In this instance it would be more policy-relevant to present estimates of disease burden for individual cities, and hence to conduct analyses at the city-level. The Australasian assessment followed this approach, and estimated excess mortality in older people for all major cities.

Less ideally, the spatial boundaries may have to be determined by the scale at which estimates of the climate-disease relationship have been prepared. If sub-populations differ markedly within a country, it may only be possible to make an assessment of risk for some sub-populations. When the Australasian assessment was conducted, quantitative estimates of the relationship between climate and diarrhoeal diseases were only available for developing country conditions. These were considered appropriate to assess the risks for indigenous people living in remote desert central Australia, but not for other sub-populations.

2. General method

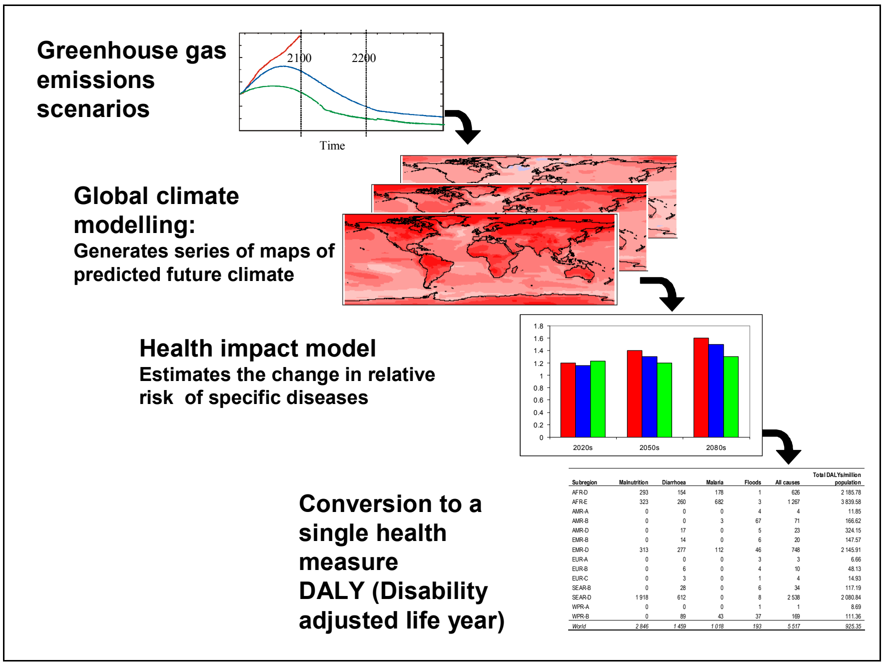
2.1 Summary of the method

Estimates of current or future burden of disease due to climate change may be made at global, regional, national or sub national levels. The main steps in estimating the disease burden are:

- *Select the scenarios and time period.* This consists of selecting a range of alternative possible futures (e.g. lower or higher rates of emissions of greenhouse gases, population growth etc.), and the timescale over which to carry out the assessment.
- *Obtain measurements of the exposure.* A series of global climate models are available that describe the changes in climate variables that are likely to result from the scenarios selected above, through time and space.
- *Identify health outcomes for assessment.* This should include health outcomes that are known to be climate sensitive, and are likely to be significant causes of ill-health within the study population over the assessment period.
- *Quantify the relationship between climate and each health outcome.* Usually based on available data on the effect of climate variations, either in space or time, on each of the selected health outcomes.
- *Link the exposure measurement to the climate-health model.* Coupling the climate projections with the quantitative models to assess possible relative changes in the health outcome.
- *Estimate burden of disease in the absence of climate change.* Using existing projections, or developing new projections, of likely future trends in disease burdens determined by non-climate factors such as economic development or future improvements in health interventions.
- *Calculate the climate change attributable burden of specific diseases.* Applying the relative changes calculated above to the estimates of the burden of each disease in the absence of climate change.

These steps are described in more detail in the following sections. A step-by-step example is given for Australasia in Section 4.

Figure 2 Overview of the process used for quantitative estimation of the burden of disease at the global level



Source: (McMichael et al., 2004)

2.2 Selecting the scenarios and time period

To calculate attributable and avoidable future burdens and the population at risk, the first step is to select plausible scenarios of the future, including changes in emissions of greenhouse gases which are the main determinants of global climate change. Greenhouse emissions are distributed reasonably homogeneously throughout the atmosphere, and hence emission scenarios are usually defined at the global level. The IPCC (2000) has developed a series of 40 scenarios of plausible future trajectories for population growth, and economic and technological development (called the SRES – *es-res* – scenarios). These are used to estimate future greenhouse gas emission levels. Use of the SRES is recommended in national assessments to aid comparison between studies.

The merits of providing a comprehensive range of emission scenarios need to be balanced against the resources entailed in conducting a larger analysis and, importantly, the purpose of the national assessment process. In many cases, national assessments will be used to inform policy for the government and private sectors, and to educate and raise awareness in the wider community. It is usually desirable to minimize complexity in the display and interpretation of information (see Box 1).

As current policy decisions will affect climate change for many decades, it is relevant to assess disease burdens over relatively long periods into the future. It is also true that projections of climate change, and of the many additional factors that affect disease rates, become less reliable further out into the future. Impact assessments are often conducted for the next three to five decades.

Box 1 Selection of scenarios and models to represent range of possible future climates in the Australasian assessment

The Australasian assessment used a subset of the available scenarios and models, chosen to represent the range of uncertainty about future conditions, while still remaining simple enough to be understandable to policy-makers. The analyses of climate change health impacts were conducted at two future time points, and used three SRES scenarios and two different climate models projections (Table 2) – a total of twelve results for each health outcome estimate. The addition of another emission scenario or climate projection to the analyses would have had a multiplicative effect on the amount of output generated.

Table 2 A matrix of the time points, scenarios and climate models used for the Australasian assessment

Timepoint	Emission Scenario*	Climate Projection Models **
2020	High (A1FI)	CSIROMk2
		EHCAM4
	Mid (A1B)	CSIROMk2
		EHCAM4
	Low (B1)	CSIROMk2
		EHCAM4
2050	High (A1FI)	CSIROMk2
		EHCAM4
	Mid (A1B)	CSIROMk2
		EHCAM4
	Low (B1)	CSIROMk2
		EHCAM4

* SRES (IPCC)
** CSIROMk2 (CSIRO Atmospheric Research, Australia); ECHAM4 (Max Planck Institute for Meteorology, Germany)

The factors influencing the choice of SRES scenarios in the Australasian assessment were (1) the availability of data: fine resolution climate model projections were only available for a subset of the 40 scenarios, and (2) an aim of representing the range of different possible futures. The *B1* story, for example, projects a relatively low rate of GHG emissions and consequently a less dramatic rate of climate change. By contrast, the *A1F1* story has the highest projected emissions and the fastest rate of change. The *A1B* story is a mid scenario between these two.

2.3 Measurements of the exposure

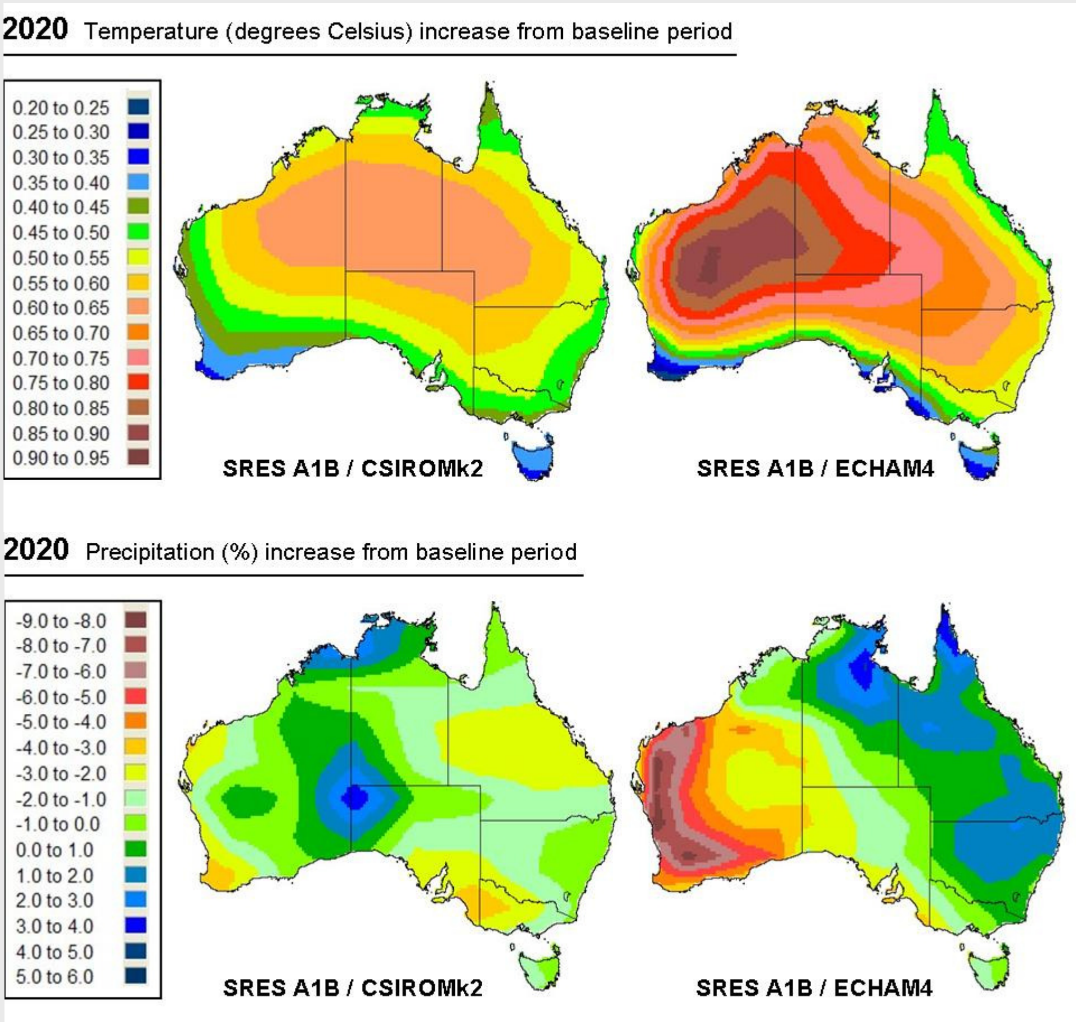
The exposure is the output of global climate models that predict the effect of future emissions scenarios on climate properties, such as temperature or precipitation. Exposure is usually expressed as how much a climate property has changed from the agreed standard baseline condition (i.e. the average of the period 1961-1990, on the assumption that this period has not been strongly affected by human actions).

A number of research groups produce global climate models that describe the projected changes in climatic conditions, and the geographical distribution associated with these different emissions. A series of six theme groups are approved by the IPCC. The IPCC website (http://www.ipcc.ch/) describes how to access the output from climate models.

Box 2 Representing the range of future exposures to climate change in the Australasian assessment

The Australian situation illustrates the variation in future climatic conditions that global climate models provide. All models agree on an Australia-wide trend of increasing temperatures, although there are differences between models in the rate of warming across parts of the continents. There is wide variation, however, among the models in the representation of future precipitation patterns. Some show large increases in rainfall, and others large decreases. All general circulation models have wide uncertainty boundaries around the estimates for rainfall. While there is agreement that rainfall will become more polarised in its distribution (i.e. more extreme) there is less certainty about the future mean level of rainfall in regions (i.e. will it become, generally, wetter or drier). The two climate simulations that were chosen represent the most strongly different patterns for the country (see Figure 3). The CSIROMk2 model projects wetter conditions in central and northern Australia, and the ECHAM4 model projects drier conditions in the west (Max Planck Institute for Meteorology).

Figure 3 Two model simulations of temperature patterns in Australia in 2020 under the A1 (mid) scenario



Both models project warming, particularly in the centre of the continent, but vary in the degree of warming projected, and the precise geographical pattern.

Model outputs are usually supplied as gridded values of predicted changes in each climate parameter (temperature, rainfall etc) for each stabilisation scenario and future time period. For example, temperature in a single grid cell may be estimated to increase by 1.3^{o}C in 2030, relative to the baseline period. Some climate software (e.g. Schlesinger and Williams, 1997) gives estimates of climate changes at the national level. It is more common, and more accurate, to estimate climate changes at the level of individual grid cells, and use Geographic Information Systems (GIS) software to overlay these on digital maps of population distributions and administrative boundaries to estimate changes in exposure for specific populations.

In mapping the distribution of climate changes, it is important to consider the appropriate scale and spatial resolution for the analysis. The grid cells used in many global climate models are too coarse to capture factors that influence climate at the scale of individual countries (typically 3.75 longitude by 2.5 degrees latitude or approximately 400 by 280 km at the equator – longitudinal cell length decreases substantially with increasing distance from the equator). For national level analysis there are two options. First, obtain higher resolution regional models of climate change. In the Australasian assessment, projections for future changes in temperature, rainfall and vapour pressure were prepared using local climate data, greenhouse gas emission scenarios and down-scaled global climate models patterns to generate country-scale scenarios at a grid size of 0.25 x 0.25 degrees – approximately 27 km^2 at the equator (CSIRO, 2001). In the absence of national models, a second option is to obtain maps of future conditions and to overlay these onto higher resolution maps of baseline climatic conditions for the country. These baseline conditions are available at 0.5 x 0.5 degree resolution at the global level (New et al., 1999; CRU, 2006) and at higher resolution for some regions (e.g. for Africa, Hutchinson et al., 1996).

Several global and national assessments have used climate projections from only one or a limited number of global climate modelling groups. A more complete representation of the uncertainty around estimating the exposure can be given by repeating the analysis with outputs of a range of models. Software programmes such as COSMIC (Schlesinger and Williams, 1997), MAGICC and SCENGEN (Wigley, 2003) are freely available, and encompass simplified versions of the main models approved by the IPCC. These can be used to give a more realistic representation of the range of currently available projections at the national level.

The value of presenting the range of current known uncertainty in the modelling of climate change impacts for national assessments has to be measured against the problems involved in communicating scientific complexity to non-scientific audiences. When presenting the results to policy makers and other groups, it is important to stress that there are no probability estimates connected to any of the IPCC SRES scenarios. In other words, the middle value of three temperature projections based on different SRES scenarios is not a more likely estimate than the other. Accordingly, it may be preferable to present the upper and lower estimates in an assessment report. This will hopefully reduce the likelihood that policy makers will drift to the middle estimate, thinking if is the most representative.

2.4 Which health outcomes should be assessed?

Health outcomes should be selected for which there is (1) evidence of sensitivity to short-term climate variability or geographic differences in climate, (2) expected public health impact within the study population.

These include diseases that have a direct physiological link with climate (e.g. cardiovascular disease), or infectious diseases where part of the transmission cycle for the pathogen occurs outside of the human host (e.g. vector-borne diseases and some diarrhoeal diseases). These diseases show a seasonal variation. Other impacts of climate change are more indirect, such as health threats arising via rising sea levels. Ideally, all health outcomes which are directly or indirectly linked to climate variability and climate change should be considered. In practice, the assessment is likely to be limited by the availability of quantitative models describing climate-health relationships.

A useful starting point is the list of outcomes considered in the global level study. These were deaths from cardiovascular disease in temperature extremes (incidence); diarrhoeal disease (incidence); malnutrition (prevalence); deaths in floods and landslides (incidence); vector-borne diseases (incidence of malaria); and people exposed to flooding from sea level rise. Many other health outcomes are understood to be affected by climate variability, and hence by climate change. For several reasons, including the indirect and complex pathways that operate between climate and disease, quantitative relationships have yet to be established for these. Table 3 shows the range of health outcomes which are known to be climate sensitive, indicating those for which quantitative relationships have been derived for either the global and /or Australasian assessment.

In specific countries, there may be other locally important climate-sensitive diseases that require further investigation of the potential effects of climate change. In Australia, for example, this would include changes in the distribution and transmission of vector borne-diseases such as Ross River virus disease, Murray Valley encephalitis, and Japanese encephalitis.

2.5 Quantify the relationship between climate and each health outcome

This involves a statistical analysis of the effect of past variations in climate on disease either in time (e.g. measuring the effect of unusually hot or cold days on death rates) or in space (comparing disease rates in areas with different climates). In such analyses it is important to account for those non-climatic influences that would also affect disease rates, such as seasonal trends unrelated to climate or variations in socio-economic conditions.

The quantitative analysis yields an estimated change in disease rates, or in the probability of disease occurrence, for each unit change in the climate variable (e.g. the increase in diarrhoea incidence per year for each degree Celsius increase in average ambient temperature). This can be used to calculate the relative risk (i.e. proportional change relative to the baseline) of each health outcome under each of the various future climate scenarios.

The appropriate methods for assessing quantitative relationships between climate and health vary, depending on whether the assessment is attempting to describe variations in diseases within already affected populations (e.g. the rate of cardiovascular disease deaths or diarrhoea cases with temperature), and/or potential spread of diseases to new populations (e.g. spread of malaria to higher altitudes and latitudes).

Table 3 Health outcomes known to be climate-sensitive, including those for which quantitative relationships were derived for the global and/or Australasian assessments

Climate effects on health	Outcome Measure	Quantitative assessment available	
		Global	Australasia
Direct impact of heat and cold	Cardiovascular disease deaths Hospital admissions	√ X	√ x
Temperature effects on food-borne disease	Diarrhoea episodes	√	√
Temperature effects on water-borne disease	Diarrhoea episodes	√	x
Temperature, rainfall effects on malaria	Malaria cases	√	√
Temperature, rainfall, humidity effects on dengue	Dengue cases	√	√
Effects of extreme rainfall and sea-level rise on flooding[a]	Fatal injuries Non-fatal injuries & mental health effects	√ X	√ x
Risk of malnutrition via changing patterns of agricultural yield	Lack of recommended daily calorie intake	√	x
Temperature, rainfall, humidity effects on other vector-borne diseases	Cases of Leishmaniasis, Filariasis, Schistosomiasis etc.	x	x
Effect of flooding and drought on food and water-borne disease	Diarrhoea episodes	x	x
Sea-level rise and reduced snowmelt impacts on freshwater availability	Water-related diseases in resident and displaced refugee populations	x	x
Risk of malnutrition via drought and flooding, pests, diseases, biodiversity loss, economic disruption	Non-availability of recommended daily calorie intake	x	x
Changes in air pollution and aeroallergen levels	Deaths and disease cases associated with air pollution, allergies	x	x
Destruction of health infrastructure in floods and storms	Increases in mortality and morbidity in affected catchment areas	x	x
Temperature and precipitation effects on incidence and intensity of forest fires	Fatal and non-fatal injuries	x	x
Temperature and precipitation effects on incidence of dust storms	Fatal and non-fatal injuries	x	x
Sea surface temperature increases affecting intensity of hurricanes	Fatal and non-fatal injuries, displaced populations	x	x
Exposure to UV radiation via slowed ozone hole recovery	Carcinomas	x	x
Emergence or spread of pathogens via climate-change-driven biodiversity loss	Cases of infectious disease	x	x

√yes
Xno
[a] Separately attributed to coastal floods, or inland floods and landslides

Subsequent sections give relationships that have already been derived for specific health outcomes at either at the global or regional level, as well as guidance for carrying out new analyses to derive more accurate and locally relevant climate health relationships.

- Temperature-related deaths
- Deaths and injuries from coastal and inland flooding
- Vector-borne diseases; malaria and dengue
- Diarrhoeal disease

The document does not present guidance for national-level assessment of one of the health outcomes covered in the global study (malnutrition), as this relies on the inputs of economic (food-trade) models which have only so far been applied for large, multi-country regions. More detail on this particular impact is given in (Parry et al., 1999; McMichael et al., 2004; Parry et al., 2005).

2.6 Link the exposure measurement to the climate-health model

Climate is geographically continuous, and values for the major meteorological elements are provided are available as grid cells on a map. To measure the effect of these exposures on human health, it is usually necessary to have population data in a gridded format.

Gridded maps of current population distribution, and projections out to 2015, can be obtained at relatively high resolution, from 0.5 degree latitude and longitude grid cells (approximately 55 km2) down to 1 km x 1 km, e.g. from the Center for International Earth Science Information Network (CIESIN) Gridded Population of the World project. In general, population estimates decrease in reliability as the area of grid cells gets larger. Projections of future population size and demographic structure further into the future are usually available at national level, either from national census agencies or from summaries developed by international agencies, such as the UN Population Division World Population Projects Database http://esa.un.org/unpp/. Population projections will decrease in reliability as the length of time from the present increases.

Depending on the study boundaries, population data may be available for city areas or sub national geographical regions. For example, to calculate the attributable burden of disease for the health outcomes in Australia, population estimates were available for the two time points at the capital city and “rest of State” levels (Australian Bureau of Statistics). Although three main population series were available, to avoid introducing additional complexity into the results only the “medium” estimates were used. These estimates were based on an assumption of low future fertility levels, and a medium level of overseas and interstate migration. For a later impact assessment which estimated health outcomes in the year 2100, Australian population projections were only available for the whole of the country (by broad age groups).

When appropriate maps of climate changes and population distributions have been obtained, GIS software can be used to overlay and link them, applying the appropriate relationships as derived above. For example, combining the temperature change in each grid cell by the estimated sensitivity of diarrhoea to each degree centigrade increase in temperature gives the estimated change in risk for that disease in that specific location. Applying this change in risk to the population of each grid cell, and averaging across the entire study population, will give an estimate of the average *per capita* change in diarrhoea rates within the population.

2.7 Calculate the climate change attributable burden of specific diseases

The change in disease burden can be estimated by multiplying (i) the estimated relative climate change to the health outcome by (ii) the total burden of disease that would have been expected to occur at the future time point, in the absence of climate change.

The simplest assumption for the expected future burden of disease in the absence of climate change is that the disease burden will remain at current levels. In this case, the proportional changes in disease risk could be applied to current disease burdens, as measured by national statistics or from the WHO. It is more realistic, however, to take account of changes in other determinants of disease rates. Most fundamentally, these include future changes in population size and characteristics (e.g. age structure and degree of urbanization). It is therefore recommended to apply the estimated relative changes in risk defined above, to projections of future populations - while clearly differentiating between the effect of population changes and climate changes on disease burdens.

Ideally, the estimates should also take into account, as far as is possible, the effects of other factors on underlying disease patterns. For example, malaria, diarrhoea and other infectious diseases are expected to decrease with socioeconomic development, and technological improvements over time. This step was not carried out for the global assessment, as projections of expected future trends in burdens of specific diseases in the absence of climate change were not available at the time. WHO has, however, recently published such estimates, at the regional level (See Table 4). The forward projections are based on general assumptions about the effect of projected changes in wealth, education and application of new technologies, and the same trend is applied to all infectious diseases, with the exception of HIV/AIDS and tuberculosis. These are useful as a first approximation, and are currently being applied to future projections at the global level. Researchers may, however, wish to develop projections of non-climatic effects on specific diseases in their own locations. This is beyond the scope of this guidance, but general techniques are described in (Mathers and Loncar, 2006), and recent work on specific diseases is referenced in the relevant sections below.

Table 4 Summary of key information sources

Data/tool	Provider	Link/contact
Climate data		
Future projections from global climate models used by the IPCC	IPCC and contributing research groups	http://www.ipcc.ch/
Simplified climate models for Personal computers:		
MAGIC/SCENGEN	University Corporation for Atmospheric Research (UCAR)	On request to UCAR
COSMIC2	University of Illinois at Urbana-Champaign; Electric Power Research Institute	On request to Electric Power Research Institute
Demographic and health data		
Gridded maps of current population distribution	Center for International Earth Science Information Network (CIESIN)	http://sedac.ciesin.columbia.edu/gpw/
Projections of future populations (national level)	UN Population Division	http://esa.un.org/unpp/
Core Demographic and Health statistics (national level)	National Census and health statistics offices	
Demographic and basic health statistics (national level)	WHO Evidence and Information for Health Policy cluster (EIP)	www.who.int/whosis/ (Core health indicators)
Current burden of specific diseases (national level)	WHO Evidence and Information for Health Policy cluster (EIP)	www.who.int/whosis/ (Burden of disease statistics)
Projected burden of specific diseases until 2030 (WHO regional level)	WHO Evidence and Information for Health Policy cluster (EIP)	www.who.int/whosis/ (Burden of disease statistics)
Data and modelling tools for malaria	Mapping Malaria risk in Africa (MARA)	www.mara.org.za/
	Malaria Atlas Project	www.map.ox.ac.uk/
Database of impacts of natural disasters	OFDA/CRED Emergency Disasters database (EM-DAT)	www.em-dat.net/

3. Detail of the method for five health outcomes

The following sections provide a detailed description on how to quantify health impacts from selected diseases assessed in either the global or Australasian assessments.

3.1 Temperature-related deaths

Temperature-related deaths are most evident as `spikes` in mortality during prolonged periods of extreme temperature such as the European heat wave of 2003 (Kosatsky, 2005). More subtle effects of temperature variations have been shown in numerous studies that have associated daily variation in meteorological conditions and mortality with a wide range of populations in temperate climates (Alderson, 1985; Green et al., 1994). Typically, people over the age of 65 are at highest risk. These studies provide evidence that the relationship between mortality and temperature can usually be described as having a reverse "J-shaped" pattern, where the trough represents the comfort zone, the short arm represents the relatively steep mortality increase at hot temperatures, and the long arm shows the increase in (mainly cardio-pulmonary) mortality with colder temperatures (McMichael et al., 2006). This pattern is repeated for other disease measures that are more difficult to relate to a quantitative disease burden, such as General Practitioner consultations (Hajat et al., 2001; Hajat and Haines, 2002). In temperate countries cardiovascular disease has the best characterized temperature mortality relationship, followed by respiratory disease and total mortality. These relationships are supported by physiological evidence of the direct links between high and low temperatures and increased blood pressure, blood viscosity and heart rate for cardiovascular disease (Keatinge, 1984; Pan et al., 1995) and broncho-constriction for pulmonary disease (Schanning et al., 1986). The strong epidemiological and physiological evidence linking temperature variations and mortality suggests that the projected increase in global average temperature, accompanied by an expected increase in variability, will lead to an overall increase in the number of deaths due to hot temperatures and a decrease in the number due to cold.

Estimating the relationship between temperature variation and mortality

If the aim of the national assessment is to estimate the aggregate effect of climate change on deaths due to thermal extremes, it will be necessary to consider both the positive and negative effects of a warming climate (i.e. a reduction in deaths during cold weather as well as increases in deaths during hot weather). However, if the aim is to identify negative impacts on vulnerable populations in order to implement adaptation measures, then it will be only necessary to separate out the negative effects.

For both purposes the same basic approach is followed. The first step consists of conducting a time-series regression of variations in (usually daily) mortality rates against variations in temperature (also daily), with controlling for confounding factors such as air pollution and secular and seasonal trends. The second step is to identify the "threshold" temperature or temperature range associated with the lowest mortality rates and the exposure-response relationship between mortality increasing, and decreasing temperatures on either side of this threshold. This will yield a heat/cold *coefficient* (i.e. the percentage increase in mortality for each degree Celsius increase in daily mean temperature above a threshold value).

Ideally, this analysis should be conducted using data for the study population of interest, as the exposure-response threshold varies across regions, depending on the temperature range and acclimatization. If local mortality statistics and, less commonly, temperature data are not available, approximate risk estimates can be generated by using the exposure-response relationship from a population living in similar climatic conditions. A crude climate classification was used for the global burden of disease study, which classified global climate into four zones (excluding the relatively unpopulated polar zone) outlined in Table 5.

Table 5 Classification of global climate into four broad zones

Zone	Climate definition	Representative daily temperature distribution	Mean annual temperature (°C) (5th–95th centile)
Hot/dry	Temperature of warmest month >30°C	Delhi	25.0 (13.5–35.2)
Warm/humid	Temperature of the coldest month >18°C, warmest month <30°C	Chiang Mai	26.3 (21.6–29.5)
Temperate	Average temperature of the coldest month <18°C and >–3°C, and average temperature of warmest month >10°C	Amsterdam	9.6 (2.0–17.8)
Cold	Average temperature of warmest month >10°C and that of coldest month <–3°C	Oslo	5 (–6.3–16.5)

There are only a limited number of published studies of exposure-response relationships that have used a daily time-series and controlled sufficiently for confounding factors. Studies on populations in tropical developing countries are particularly scarce. Table 6 summarizes the relationships applied in the global burden of disease study, based on work by Kunst and others (Kunst et al., 1993) for the temperate countries, and the ISOTHURM group (ISOTHURM, 2002) for the tropical and arid countries.

Table 6 Summary of temperature-mortality relationships derived from the literature
Percent change in mortality for a 1 °C change in mean daily temperature above or below the specified threshold

		% Change in All-medical-cause mortality[a]		% Change in Cardiovascular mortality	
	Threshold (°C)	Hot	Cold	Hot	Cold
Arid (hot and dry)	23	3.0	1.4	NA	NA
Tropical (warm humid)	29	5.5	5.7	NA	NA
Temperate	16	NA	NA	2.6	2.9
Cool temperate	16	NA	NA	1.1	0.5

[a] Excludes external causes (deaths by injury and poisoning)
NA: data not available

Although the global exposure-response estimate could be used for approximate measures of risk at the national level, much more accurate and useful measures can be generated from local data. Small countries with only one major climate zone could use a single baseline daily temperature distribution (for an average year) which would generate a single exposure-response relationship. In very large countries, a variety of major climate zones are represented, and daily temperatures, acclimatization, and adaptation options (such as housing types, cooling and heating methods) vary substantially between cities. For the purpose of policy and communication it may be more appropriate to conduct separate analyses within selected large cities from each climate zone.

Estimating temperature-related mortality under 'baseline' and future climate

Once the exposure-mortality relationship between temperature variations and mortality has been established, the next steps involve: (1) measuring the frequency with which daily temperatures occur above or below the comfort range, and (2) estimating the average annual number of heat and cold-attributable deaths in the study population.

For the first step, several different methods are available for estimating the average daily temperature distribution (both maximum and minimum). A long meteorological dataset is desirable, ideally using data for more than ten years during the baseline period 1961-1990. Temperature data can be in the form of observations from central-city weather stations across the study cities. For small countries or sub-national areas, an interpolated data surface can also be used (with temperature values calculated for grid cells that can be averaged to provide area-wide daily values). These types of data are usually collected by the national meteorological organization. Not all cities will have continuous high-quality meteorological records from the central city weather station. For many cities temperature data have been historically collected at airport stations. In such cases, the temperature records are likely to under-estimate the actual temperature due to the "heat-island" effect. Cities – with thermal mass (from buildings and roads) and energy production (from transport and industry) – usually record higher daytime and night-time temperatures relative to outlying suburbs. However, in general a hot day in the outer suburbs will also be a hot day in the city centre, and the variations from day to day recorded at the airport can be assumed to represent the day to day variations in the urban centre (even though these latter may be several degrees higher). For high density city populations, temperature records obtained from the airport can thus be assumed to give a lower estimate of the true effect of heat on mortality levels.

For the second step, mean annual mortality figures are required for each population (i.e. city, large area, or country). The true number of annual deaths will be more accurately reflected if a time period immediately prior to the assessment is used for the estimate (i.e. death records for the preceding 5 years).

The number of deaths attributable to temperature in a given population (e.g. one city) can be estimated by:

[Eqn 1] $A = ([EM_{HOT} * (Tmp>Thresh_{HOT})] + [EM_{COLD} * (Tmp>Thresh_{COLD})]) * M$

where:

A	Average number of deaths attributable to temperature each year.
EM_{HOT}	The percentage increase in deaths for each degree Celsius temperature increase *above* the hot threshold (i.e. the exposure-mortality relationship)
EM_{COLD}	The percentage increase in deaths for each degree Celsius temperature decrease *below* the cold threshold (i.e. the exposure-mortality relationship)
$Thresh_{HOT}$	Frequency of days in the period where the temperature (Tmp) *exceeds* the hot threshold (Thresh)
$Thresh_{COLD}$	Frequency of days in the period where the temperature (Tmp) is *below* the cold threshold (Thresh)
M	Mean annual all-cause mortality in the study population (e.g. the 65+ age group)

The final stage consists of using future projections from global climate models to estimate distributions of daily temperature values in the future, and then applying the exposure-mortality relationships to calculate the proportional change in mortality for both hot and cold extremes. This consists of reapplying equation [1] above with the projected future temperature distribution. Ideally the estimation for the future should also take account of population changes, i.e. using:

[Eqn 2] $A = [EM_{HOT} * (Tmp>Thresh_{HOT}) * M * P] + [EM_{COLD} * (Tmp>Thresh_{COLD}) * M * P]$

where

P Proportional change in population size, relative to the baseline.

Results should report how temperature-associated mortality changes with *and* without adjustment for population change.

Box 3 Assessing current and future temperature-related deaths in Australasia

The Australasian assessment used a Poisson multiple regression analysis with daily mortality as the outcome variable and daily maximum and minimum temperatures as explanatory variables. For example, the time-series analysis for the city of Christchurch in New Zealand (a temperate city) showed that deaths attributable to cold temperatures commenced below 0°C (at a rate of 0.8% per degree below that). At the hot end, deaths started at 28°C and increased by 3% per degree above that point. This relationship was applied to all temperate cities in the region (i.e. including those in Australia). For the tropical cities of Darwin and Cairns (northern Australia) temperature-attributable mortality increased by 10% per degree above 34°C, and no threshold was evident for minimum temperatures.

The accuracy of exposure-response estimates can be improved by controlling for non-climatic variables that would modify the association. These relationships reflect the independently remaining effects after air pollution (PM_{10}, a measure of particulate pollution) and seasonal patterns of mortality were accounted for. Although factors such as housing type, cooling and heating methods may vary *between* particular cities, for the Australasian assessment it was assumed that these factors did not vary significantly *within* cities over the study period (5-10 years).

Average annual all-cause mortality figures for people aged 65 and over for the years 1997 to 1999 were combined with annual population figures to derive the baseline mortality rate (per city).

Future average annual maximum and minimum temperature increases were estimated for each city area. Two future mortality analyses were calculated. The first adjusted for the projected change in population size in the 65+ age group (city increases or decreases in the future size of this group were taken from Australian Bureau of Statistics projections). The second analysis assumed that the population size and structure in the future years would remain the same as in the baseline year.

Main sources of uncertainty

The temperature threshold for mortality varies between locations (e.g. studies on various United States' cities (Braga et al., 2001; Braga et al., 2002)), which suggests that people are able to acclimatise and adapt to climatic conditions. The limits to this adaptive capacity have not been quantified, nor have a wide range of populations been studied. It is likely that the process of population acclimatisation and adaptation (increased use of air conditioners, additional intake of fluids, changed work hours, better building insulation and design, etc) will affect the estimate of future heat and cold deaths. These factors will strongly influence public health policy and planning, such as development of heat-forecasting and emergency response systems, heat-related illness management plans, energy efficiency and building code guidelines, and education for behavioural change. The approach described here provides information about the expected change in mortality in the *absence* of adaptation options. Each of those strategies listed above, if enacted, would be likely to reduce the susceptibility of vulnerable groups in future.

Related to this, there is uncertainty about the effect that changing socio-economic conditions will have on disease rates. Some evidence indicates that affluent sub-populations can be partially protected from extremely hot temperatures by the use of air conditioners (e.g. studies in Chicago, USA (Semenza et al., 1996)). However, research in São Paulo, Brazil (Gouveia et al., 2003), which has a wider range of socio-economic conditions, failed to detect a difference in susceptibility. Even if people are able to acclimatise to the mean rise in future temperatures, the nature of extreme heatwaves is such that people often do not have time to adapt to high temperatures (Stott et al., 2004). Changing patterns of predisposing conditions, such as hypertension, also affect people's vulnerability to heat stress.

3.2 Deaths and injuries from coastal and inland flooding

Floods and storms are currently a major cause of death in some regions of the world (OFDA/CRED, 2006). There is evidence that long-term weather cycles (such as the ENSO quasi-periodic cycle) are significantly correlated with the incidence of deaths and injuries due to natural disasters (Bouma et al., 1997; Kovats et al., 1999). The frequency of large floods during extreme wet seasons has increased over the 20th century in the world's largest catchment areas (Milly et al., 2002). The predicted trend towards increasingly variable rainfall is likely to increase the risk of weather-related natural disasters, such as floods, by an additional several-fold by the middle of the 21st Century in several regions (Palmer and Ralsanen, 2002). Continuing sea level rise will also contribute, by making unprotected low-lying populations increasingly vulnerable to coastal floods. It is possible that climate change may also change the frequency of other weather disasters, such as wind storms (Knutson and Tuleya, 2004), but there is less agreement about the nature and magnitude of change.

Sea level rise and increasingly variable weather are therefore likely to directly increase the risk of death and injury during events. In addition, there is the likely increase in health-related impacts through population displacement, economic damage to public health infrastructure, and psychological trauma (Jovel, 1989; WHO, 1992; Menne et al., 1999). Despite the clear links between climate change, weather extremes and health impacts there has been very little research on their quantitative relationships. However, it is possible to generate conservative estimates of the potential health effects that are consistent with current information on these risks.

Estimating exposure to flooding at baseline climate

In contrast to other health outcomes, the baseline burden of deaths from flooding has not been estimated by the WHO. It can, however, be calculated from a combination of international as well as national sources. Disaster databases are becoming increasingly used to help prioritise international action to reduce disaster risk. Four main international disaster databases are EM-DAT, NatCat, Sigma and DesInventar. Of these, the most comprehensive source at the global level is the OFDA/CRED EM-DAT (emergency-disasters) database, which records the number of deaths and injuries attributed to each natural disaster in countries worldwide over the last 100 years (as reported by the media or aid agencies). In this database, disasters are defined as events that resulted in at least one of the following conditions: (1) >10 people killed, (2) >200 injured, (3) a call for international assistance. Despite the apparently comprehensive nature of this database, all disaster databases are subject to under-reporting in general as well as regional reporting biases (there is less detailed and accurate estimates for developing countries). The (IFRC, 2005) provides a fuller discussion of the issues. Impact estimates derived from these or similar sources will inevitably be conservative (Noji, 1997).

Climate change is likely to have different effects on coastal floods (mainly influenced by sea level rise) and inland floods (through changes in precipitation). It is necessary to separate the impacts of these different kinds of events in the EM-DAT database. For the global assessment events in the database were classified as 'coastal' or 'inland' where sufficient geographical information was provided. The effects from the remaining flood events were allocated in proportion to those in each of these two classifications. If this database is used for an assessment, it is recommended that only *deaths* from flooding are used, and that *injuries* are excluded, as these figures are considered particularly unreliable for floods (D. Guha-Sapir, OFDA/CRED, personal communication, 2002). The annual incidence of flood death under baseline climate conditions can be calculated by dividing the annual average deaths across a long period (preferably more than 20 years) by the annual average population over that time.

Flood mortality incidence will alter over time, irrespective of climate change, as the factors that decrease vulnerability (such as improving flood defences as populations become richer) and increase it (such as increasing population density in coastal zones and other flood-prone areas) also change. Future estimates should ideally be adjusted for these effects to get a more realistic estimate of impacts of flood risk. Some global models of coastal flooding risk have attempted to incorporate several of these factors, including the effect of projected changes in population distribution and density along the coastline, and assumptions about improving coastal defences in line with increasing gross national product (GNP) (e.g. Nicholls et al., 1999).

Such vulnerability effects have not yet been included in modelling for inland flooding. However, (Yohe and Tol, 2002) conducted a cross-sectional analysis of the effect of *per capita* income on the incidence of death due to all natural disasters (as reported in the EM-DAT database) for the period 1990–2000. They concluded that increasing wealth has a protective effect, best described by:

$$\text{Ln (proportion of population killed per decade)} = 4.7271 - 0.3858\ (\text{Ln GDP per capita})$$

This is not an ideal adjustment, as the income effect estimate was marginally non-significant at the 5% level ($P < 0.07$). However, it is the only available estimate of the role of economic development, it is one that is generic to all natural disasters, and is not influenced by the magnitude of the physical hazard. Long-term economic development scenarios (i.e. future gross domestic or gross national product) that are linked to the IPCC SRES scenarios (Nakicenovic, 2000) can be obtained at regional level from (IPCC Data Distribution Centre, 2006), and at national level from sources such as. (IMAGE Team, 2002).

Estimating exposure to flooding in future

Coastal flooding

More research has been undertaken to estimate the effects of sea level rise on coastal flooding than on the effect of changing precipitation regimes on the frequency and severity of inland flooding. Two studies have used global models to estimate sea level rise under several IPCC scenarios (Hoozemans and Hulsburgen, 1995; Nicholls et al., 1999). However, the health impacts associated with exposure to coastal flooding have not been investigated in detail. Both studies applied sea level rise projections to topographical and population distribution maps to estimate the change in annual incidence of people exposed to flooding (by country). These global models have been shown to be relatively accurate in validations against more detailed assessments that were conducted at the national level (summarized in Nicholls et al., 1999). The global assessment used the Nicholls results to estimate the annual population exposed to flooding, and the Australasian assessment reported these findings.

Inland flooding

Inland floods and landslides are not affected by sea level rise but instead are influenced by the frequency of intense rainfall. At the local level, flood risk is a function of the temporal pattern of rainfall (i.e. not only by the total amount of rain across a month, but by the peak amount falling in a week, a day or an hour), the topography of an area, and social aspects of vulnerability (Kundzewicz and Kaczmarek, 2000). This relationship is poorly researched (Pielke, 1999), with few published analyses of the relationship between the intensity of precipitation, the likelihood of a disaster, and the magnitude of the health consequences.

Despite the absence of quantitative studies, there is a demonstrated causal link between floods and health outcomes. It is therefore reasonable to assume that changes in precipitation patterns will impact on deaths and injuries in floods. In lieu of an existing method, the global assessment method assumed that deaths and injuries from flooding are directly related. That is, if the risk of exposure to flooding doubles the number of deaths and injuries from these events will also double. It was assumed, *a priori,* that the health impacts of inland flooding occur when populations are exposed to monthly rainfall exceeding the 1 in 10 year limit (i.e. the upper 99.2% CI).

This can be estimated using geographic information systems software by:

1) Using a grid map of population distribution as the basis for estimating exposure to extreme precipitation.
2) Using monthly rainfall data from, as a minimum, the period 1961–1990 (i.e. the baseline climate) to calculate the mean and standard deviation in precipitation for each population grid cell, and using this to estimate the upper 99.2% confidence interval (i.e. the 1 in 10 year limit).
3) Repeating the process for the selected climate change scenarios and time points.
4) Calculating the difference, in standard deviates of the new distribution, between the new mean and the previously defined "1 in 10 year limit". This is given by the formula:

$$\text{Difference} = [(X_1 + 2.41 * u_1) - X_2]/u_2$$

where:

X_1, u_1 = mean and standard *deviation* from 1961–1990

X_2, u_2 = mean and standard deviation under new scenario.

5) Calculating the probability that the "1 in 10 year limit under baseline climate" will be exceeded in any one month under the new distribution.
6) Calculating the relative change in frequency of exceeding the 1 in 10 year limit, by dividing by the frequency with which this limit is exceeded under the baseline scenario (i.e. dividing by 1-.992 = 0.008).
7) The results can then be weighted by the population in each cell, and averaged across the study population, to give the final measure of exposure: the change in the frequency with which each person in the population experiences a 1 in 10 year rainfall month.
8) The expected effect of climate change on deaths and injuries from floods can be calculated by multiplying the baseline incidence with the relative change in the frequency of these events.

As for other impacts, this global approach can be made more detailed at the national level, depending on the availability of data. In addition, the procedure described will only generate estimates of the immediate acute consequences of natural disasters, just one component of the total attributable disease burden from flooding. Floods have important effects through mental health, social and economic impacts, although these secondary effects are not yet well quantified. Plausible effects include: repercussions from vulnerabilities in the agricultural sector (such as crop damage, changing crop suitability or the enhanced spread of agricultural pests); in water resources (availability, quality, agricultural irrigation and power generation); on the coastal zone (loss of land, damage to infrastructure resulting from coastal erosion and flooding); to ecosystems (affecting some infectious disease outbreaks, (Epstein, 1999); the effect of sequential disasters on public health infrastructure; and the longer term-effects associated with post-traumatic stress (Phifer, 1990), population displacement, and food shortages (UN-DMTP, 1990; WHO/PTC, 1995).

Although not a direct health impact, it can be illustrative to show the costs of agricultural, housing, and infrastructure losses as these also represent costs to individuals, communities, state governments, and the insurance industry. The EM-DAT database provides a crude estimate of some of these costs. NatCat and Sigma are two databases managed by Munich Re and Swiss Re respectively, two of the world's largest reinsurance companies, and provide more details. In general, however, data are very incomplete for economic losses. Over the past three decades, macro-economic losses were reported for less than 30 per cent of all natural disasters – with least data for developing countries – and there is no standard methodology for reporting such losses. Not surprisingly, there is limited information on countries with low insurance density. This reduces their data coverage for Africa, Asia and Latin America, particularly in rural areas.

Box 4 Estimating effects of coastal and inland flooding in Australia

The Australasian assessment shows the advantages of supplementing or replacing global with national data, when such data exist and are reliable. In this assessment the rate of deaths and injuries attributable to extreme rainfall events was calculated with data from two sources: the EM-DAT global database (OFDA/CRED, 2006) and the Emergency Management Australia database (Emergency Management Australia, 2006). The latter is the principal ongoing collection of natural disaster events in Australia. The two data sets were combined to maximise the available information on place, time and climatic conditions relating to deaths and injuries. Reported deaths due to flood and severe storms were available from 1970 to 2001. Deaths listed from tropical cyclones or severe storms at sea were not included. Average annual incidence rates for the 32 year period were calculated for state and national populations, as the data were less reliable at a finer spatial resolution. Population figures were obtained from the Australian Bureau of Statistics website.

In the Australasian assessment the analyses were conducted at a finer spatial scale (0.25° by 0.25° grid cell) than for the global assessment. Rainfall is highly variable, and a longer time-series of baseline rainfall observations (preferably 30 years minimum) will improve the accuracy of the baseline estimate. In the Australasian assessment, the rainfall mean and standard deviations for each grid cell were derived from observed monthly rainfall from 1961 to 1970 (120 months).

Main sources of uncertainty

- The main limitation of this method is the failure to account for expected changes in rainfall intensity. Current global climate models projections provide estimates of mean changes in distribution (monthly and annual averages), but do not yet provide reliable estimates of the variance. Rainfall, regardless of whether it increases or decreases in total amount, is likely to become more variable in distribution. Therefore this method may underestimate the impact in regions where rainfall totals will decrease.
- A second weakness for the global assessment was the very short time period from which the baseline rainfall mean and variability were estimated. Ideally, monthly data for at least the whole of the standard thirty year "climate normal" period (1961 to 1990) should be used.
- The EM-DAT disaster database is constrained by the lack of systematic, standardized local and national disaster data collection (IFRC, 2005). This is a particular challenge for EM-DAT, which draws from international sources built on local and national data. EM-DAT catalogues events by country, making it difficult to identify sub-national patterns of disaster loss.
- Flood deaths are generally not evenly distributed by sex and age. In Australia, the greatest proportion of flood-related deaths have been in people aged under 25 and over 59, reflecting a greater propensity for risk-taking in young adults, and increased risk with immobility (Coates, 1999). Historically, males have been at much higher risk than females, although this is reportedly decreasing. Risk analysis would be improved if baseline age and sex rates were available.

- Vulnerability to drowning is clearly strongly dependent on infrastructure, lifestyle, attitudes towards perceived risks, and settlement trends (e.g. building in flood-prone areas). This vulnerability is likely to change significantly over short to mid-time scales.
- The assumption that flood risk increases as rainfall totals increase, and that the threshold level of the upper 99.2 percentile is a critical indicator of floods, appears reasonable but has not been tested. Flood risk is a function both of intensity and duration, as well as typographic concentration. The two main types of floods (flash floods and riverine floods) may well show differences in critical levels.

3.3 Malaria

Climate and vector-borne diseases

Viruses, bacteria, protozoa and helminths transmitted by biting insects and other vectors are among the most important causes of ill-health in tropical regions (WHO, 2004b). Climate affects the reproduction and survival rates of both the infectious agents and their vectors (e.g. reviews by (Martens, 1998; Massad and Forattini, 1998), and hence their ability to infect humans. This is reflected in the temporal correlations between vector-borne disease rates and weather fluctuations over weeks, months or years (e.g. Christophers, 1911; MacDonald, 1957; Kuhn et al., 2003; WHO, 2005) and also the close geographical correlations between climatic factors and the distribution of diseases (e.g. Rogers and Randolph, 2000; Hales et al., 2002); review by (Kovats et al., 2000). Climate does not act on the transmission of vector-borne infections in isolation: socio-economic conditions, control programmes, human immunity and other environmental conditions also influence disease rates. In some cases these may have more influence than global climate trends, particularly at small spatial scales (Sutherst, 1998; Mouchet and Manguin, 1999; Randolph et al., 2000; Rogers and Randolph, 2000; Reiter, 2001).

The IPCC has reviewed the observed and predicted effects of climate variability and change in the context of the other factors listed above (IPCC, 2001a). It concludes that climate change is likely to expand the geographical distribution of several vector-borne diseases, including malaria, dengue and leishmaniasis to higher altitudes (high confidence) and higher latitudes with limited public health defences (medium/low confidence), and to extend the transmission seasons in some locations (medium/high confidence). For some vector-borne diseases in some locations, climate change may decrease transmission by reductions in rainfall or temperatures too high for transmission (medium/low confidence).

As for other diseases, the most reliable basis for estimating climate change effects should come from information on the relationships between variations in climate and disease in the past or present. Several studies have used such data to model the effect of projected climate change on the distribution of vector-borne diseases, or on risk within existing or predicted newly endemic areas. The main approaches are outlined below. Although all the transmission of all vector-borne diseases is likely to respond in some way to climate change, there has only been significant quantitative modelling work for falciparum malaria, and, to a lesser extent, dengue. The global assessment estimated world-wide climate change impacts for malaria. The Australasian assessment estimated both malaria and dengue impacts (discussed later).

Alternative approaches to quantify the relationships between climate and vector-borne disease

The methods for modelling climate effects on vector-borne diseases can be broadly classified into three groups:

1. **Biological models**. This approach uses laboratory data to define the relationship between meteorological factors (typically temperature, but in some cases also rainfall and humidity) and individual components of the infection transmission cycle. The most import of these are the rate of development of the parasite (Martin and Lefebvre, 1995), and the survival probability and biting frequency of the vector (Martens et al., 1995a; Martens et al., 1995b; Jetten et al., 1996; Martens et al., 1999). Standard equations describing the vectorial capacity of a vector population (Garrett-Jones, 1964; Dye, 1992) can be used to give an aggregate measure of how climate variability or change can bring about proportional changes in transmission intensity.

With complete information on both climatic and non-climatic influences on the transmission cycle, such biological models could potentially give comprehensive assessments of disease risks under future climate scenarios. The models that have been developed so far, however, generally lack information on one or more risk factors (e.g. the effect of socioeconomic factors or control programmes) acting on one or more components of the transmission cycle (e.g. vector density). This makes it difficult to use them to define either the limits of disease transmission, or the intensity of transmission within these zones.

2. **Statistical models**. It is also possible to define the relationship between climate variables and disease incidence or distribution in purely statistical terms. This approach involves mapping the geographical distribution of the disease against the distribution of climate variables, and carrying out a regression analysis to characterize the climatic conditions that are associated with presence vs. absence of disease, or with different levels of disease transmission (see Rogers and Randolph, 2000) for malaria, (Hales et al., 2002) for dengue). The main advantage of this approach is that it is entirely driven by a transparent statistical relationship between climate and disease distributions. It is also theoretically possible to include other, non-climatic, explanatory variables or confounders in the model.

The main limitation of this approach is that it depends on the quality of the distribution maps available to define, and also to test, the quantitative relationships. Disease data are often at low resolution and of uncertain accuracy (e.g. large regions are often defined as uniformly endemic or non-endemic, whereas in reality transmission is either absent or varies markedly within endemic zones). Data on other determinants (e.g. socioeconomic status or control programmes) are seldom included in statistical models.

3. **Combined biological and statistical models**. A third approach, exemplified in the work by the MARA (*Mapping malaria risk in Africa*) research group, combines elements of both the biological and statistical methods. This combines laboratory data on temperature-parasite relationships with field observations of climatic cut-offs for disease transmission, to define either a 'fuzzy logic' measure of climatic suitability for malaria transmission, or defined limits (Craig et al., 1999; Tanser et al., 2003). These relationships can be applied to climate and population distribution maps to define populations living in different levels of climate suitability for disease transmission, for different months of the year. The main advantages of this approach are that (i) it does not rely on complete characterization of the transmission cycle, (ii) avoids using coarse disease distribution maps to define the statistical relationships between climate and disease, and (iii) the final outputs, of climate suitability and/or number of person-months exposed, are known to be correlated with disease risk (Omumbo et al., 2004).

The main limitations are that climate thresholds for mosquito and parasite effects in the model are defined through laboratory data and only a small number of field studies. This may affect the accuracy of the estimate.

There is no simple agreement on a “best practice” approach to modelling the impact of climate change on vector-borne diseases. The choice of which approach to use will be guided by the particular research questions for an impact assessment and the data that are available. In addition, some limitations are shared by all of the approaches as applied so far – such as not accounting for non-climatic determinants or the variation in climate-disease relationships between locations, the likely non-linear relationship between the final outcome of the model and disease burden, and no or limited validation against independent data (McMichael et al., 2004; Reiter et al., 2004).

Available quantitative models of climate-malaria relationships

The global assessment used the MARA model, as described by (Tanser et al., 2003) (see Table 7) to estimate malaria impacts. This approach was selected because it came closest to assessing the criteria described above, and particularly because it is the only model that has been validated against truly independent data – at least throughout Africa, where the majority of the malaria burden occurs.

The first step in applying the model is to import gridded maps of climate conditions, by month for the baseline period (e.g. 1961-1990) into GIS software, as described in section 2.3. Using standard software functions, it is then possible to apply the following decision-rules to each grid cell, for each month, to determine whether the climate is considered suitable for *Plasmodium falciparum* transmission.

Table 7 Criteria used to calculate months suitable for *P. falciparum* malaria transmission in Africa

Simulated effect	Variable	Threshold
Parasite development and vector survival temperature	Moving average	≥ (19·5ºC + yearly SD of mean monthly temperature)
Frost	Minimum yearly temperature	≥ 5ºC
Availability of vector breeding sites	Moving average rainfall	≥ 60 mm
Catalyst month	Moving average rainfall	At least 1 month ≥ 80 mm
Parasite reservoir (also simulated by the differential temperature threshold imposed)	1 month interruption in transmission (as predicted by climate thresholds)	Automatically assigned transmission status

Source (Tanser et al., 2003)

Grid cells that meet the defined criteria can be aggregated to give the geographical area that is considered climatically suitable for falciparum malaria transmission. The next stage is then to overlay maps of population distribution (see section 2.4), within the GIS, in order to give a measure of population exposure. Standard software functions can be applied to combine data from the two gridded data sets, to generate tables of the number of people living in areas that are suitable for malaria transmission in one or more months of the year. The global study assessed the number of people living in areas suitable for malaria transmission for at least one month of the year. More recent studies (Tanser et al., 2003) have calculated the total number of person-months spent in conditions suitable for malaria transmission, throughout Africa.

Researchers need to consider whether these general rules give a meaningful description of the relationship between climate and malaria for their own population of interest. For example, the validation of the MARA model suggests it can reasonably be applied anywhere in Africa, and earlier versions have been widely used at the continental and country levels for studies of the effect of climate on falciparum malaria (e.g. Small et al., 2003). The MARA models may also potentially give reasonable predictive accuracy in other areas of the world, but this remains to be tested. In each case, local level validation of the selected model would increase confidence in any results obtained.

If researchers are not satisfied that such general models are relevant, then new statistical or biological models can be developed, based on more locally appropriate data. Detailed descriptions of approaches to model building are beyond the scope of this guidance but some general principles apply. Studies should ideally (i) use large, reliable, and high resolution datasets to define the baseline climate-disease relationships, (ii) consider the role of non-climatic risk factors in influencing the model outcome (e.g. variation in socio-economic status, land-use, host availability or control programmes across the region), (iii) provide an output measure that is related as closely as possible to the clinical burden of disease, and (iv) validate the model against independent data (if a model cannot describe the past or present reasonably well, it will not provide useful information about future impacts).

Box 5 Applying locally appropriate models for assessing vector-borne disease risk in Australasia

Global malaria models would be too coarse for the sub-national policy-level requirements of many national assessments. The Australasian assessment used an enhanced type of biological model called CLIMEX (Sutherst et al., 2004). This model takes the current known distribution, abundance, and phenology of the malaria mosquito as evidence of the climatic constraints that operate on its breeding and survival – and hence of its essential climatic requirements. The current distribution of a mosquito species obviously also includes influences that human activities have had, over time, on restricting and expanding the environments available for breeding. These include changes in human settlements, water supply, vector control practices, deforestation and other forms of land use changes. Therefore the CLIMEX modelling approach, by virtue of working from the current mosquito distribution, already includes an element of human adaptation (although not at the level of case treatment or prevention behaviours). It was assumed that at least the present adaptations to malaria will remain in the future. The quality of this type of a model is dependent on regular observations of mosquitoes at the fringes of the known distribution, to be alert to changes in habitat.

Estimating the future risk of malaria

The effect of climate changes on malaria risk can be assessed by replacing the baseline climate conditions with alternative climate scenarios, and re-applying the quantitative model of the climate-malaria relationship.

Current models provide a measure of changing exposure to malaria, rather than a complete measure of infection incidence or disease burden. If the latter are required, it will be necessary to make an assumption about the relationship between changes in exposure and in disease burden. The simplest and most parsimonious method, applied in the global study, is to assume that proportional changes in exposure (e.g. proportion of people livening in areas climatically suitable for malaria), are directly related to proportional changes in disease burden. For example if climate change in a particular region is estimated to cause a 20% increase in the number of people living in areas that are defined as climatically suitable for malaria transmission, then this is most likely to lead to a 20% increase in the malaria disease burden, compared to the situation if climate change did not occur. This proportional change can be applied to the estimated disease burden in the absence of climate change. Estimates of current burden of malaria at the national level are usually available from national statistics, or from WHO.

For estimates of future impacts, it is necessary to apply these proportional changes to projections of what is likely to happen to malaria in the absence of climate change. The simplest assumption is that the disease burden will remain at current levels. It is more realistic, however, to take account of other likely changes in other determinants of malaria, such as population size and structure, as well as socioeconomic changes and technological advances. Although these necessarily add another dimension of uncertainty, they are likely increase relevance to policy-makers. Whatever final outcome measure is used, it can be informative to show estimates with and without changes in other determinants, to differentiate the effect of climate change from these other influences.

Estimates of the effects of changes major non-climatic influences (changes in wealth, education levels, application of new technologies) on burdens of infectious diseases, including malaria, are available at the level of WHO regions, out to the year 2030 (WHO, 2006a). Researchers who wish to develop more locally-relevant estimates of future trends are referred to the methods in (Mathers and Loncar, 2006), and in studies examining climatic effects on malaria in Africa in the context of other changes, such as population growth and urbanization (Hay et al., 2006).

Main sources of uncertainty

In addition to the uncertainties discussed, there are two others that apply particularly to vector-borne burden of disease assessment. First, the ability to adjust future malaria risk models for the effect of non-climatic factors (such as changes in land-use, housing conditions, and the coverage of vaccination or curative treatment) on disease is almost non-existent. This uncertainty can be reduced by including these main variables, or proxies for them, in the baseline modelling of the climate-disease relationship (e.g. Kuhn et al., 2003). Another method is to restrict projections of future risk to areas where it is expected that poor socio-economic conditions will continue to enable transmission to occur. For example, climate is already potentially suitable for the transmission of malaria in many temperate countries, yet the disease is prevented from occurring because of sufficiently high living conditions and health services. The global assessment did not investigate the future risk of malaria in those countries, on the assumption that it was not plausible (IPCC, 2001b).

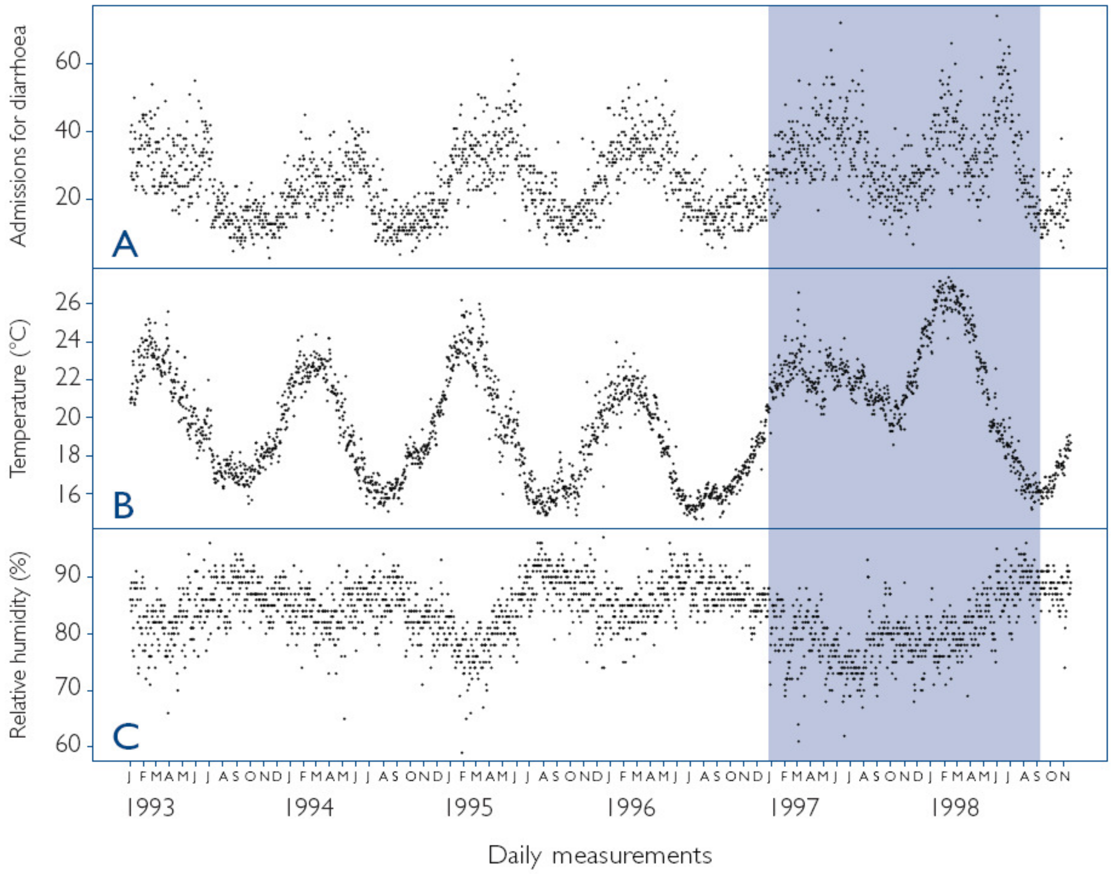
Second, the assumption that a change in incidence will vary in relation to the predicted change in population at risk is reasonable (where more people are exposed there is often a higher disease incidence and burden), but can only give a preliminary first approximation of effects on disease burdens. It may underestimate the effects of an increase in transmission within already at-risk populations. Alternatively, this assumption may overestimate the risk in other circumstances. Increasing vectorial capacity promotes herd immunity (Rogers et al., 2002) and causes first infections to occur earlier in life when, for some diseases, patients suffer less severe clinical symptoms. This potentially confers immunity on the more clinically vulnerable older age-groups (Coleman et al., 2001). This uncertainty could be narrowed by further detailed studies of the relationship between climate suitability, infection incidence, and clinical disease burdens.

3.4 Diarrhoeal disease

Diarrhoeal pathogens are highly sensitive to variations in climate, and epidemiological studies in many sites have shown strong seasonal patterns of disease (Drasar et al., 1978). Despite this, few studies have quantified this relationship. Regression analyses of weather variations and either all-cause diarrhoea, or subsets of overall diarrhoea burdens, have been carried out in a limited number of sites (Checkley et al., 2000; Singh et al., 2001; Kovats et al., 2004). All studies demonstrate strong climate sensitivity. This is consistent with observations of the direct effects of climate variables on the causative agents. Temperature and relative humidity have a direct influence on the rate of survival and replication of bacterial and protozoan pathogens, and on the survival of enteroviruses in the environment (Blaser et al., 1995). Rainfall may affect the frequency and level of contamination of drinking water (Curriero et al., 2001)).

The relationship between climate variability and diarrhoea is mediated by a range of local factors, the most important being the quality of water and sanitation coverage. This factor affects the incidence of diarrhoea, the relative dominance of different transmission routes (e.g. via water, food, or direct contact), the likelihood that extreme precipitation will lead to contamination of water supplies, and the types of pathogens that cause diarrhoea.

Figure 4 Daily time series of admissions for diarrhoea at a pediatric institute, temperature, and relative humidity, in Lima, Peru
1 January 1993 - 15 November 1998



Source: (Checkley et al., 2000)

Quantifying the relationships between climate and diarrhoea

An approximate estimate of the effect of temperature on diarrhoea in developing countries is available from the global burden of disease assessment, based on the two available time series studies. (Checkley et al., 2000), using daily data from Lima, Peru, showed that pediatric hospitalisations for diarrhoea increased by 8% for every 1°C increase in temperature (averaged across all seasons). Singh et al. (2001), using monthly data from

Fiji, showed that diarrhoea notifications increased by approximately 3% per 1°C increase in temperature.

It is therefore reasonable to estimate that in developing countries, diarrhoea incidence will increase by approximately 5% per degree Celsius increase in temperature. In this case, countries are considered as developing if they have a GDP equal to or lower than that in the richer of the two study countries at the time of the study (US$6000/year in 1990 US dollars).

Although there are studies of the effects of climate on particular subsets of diarrhoea (e.g. salmonellosis) in developed countries, there are currently no published studies that measure the climate effects on total diarrhoeal burdens in these regions. The effect of higher levels of water and sanitation coverage is likely to make these very different, and likely less temperature sensitive, than in poorer regions. It is therefore a reasonable, but conservative, assumption that increasing temperatures will not lead to an increased burden of diarrhoeal disease in developed countries.

As for other diseases, researchers should consider whether the general relationships described above from the global study are likely to give a reasonable description of climate-disease relationships in their own study area. Accuracy could potentially be improved by using local data to carry out time-series or cross-sectional analysis of the association between climate variations and diarrhoea. The main general considerations are that these should ideally (i) be based on local meteorological data at high temporal and spatial resolution (e.g. daily or weekly data from local meteorological stations), (ii) use diarrhoea data that is based on standardised diagnostic criteria, and be representative of the study population (e.g. national health surveillance services for countries or large areas, or from specific sites such as hospitals), (iii) control for the effects of non-climatic seasonal variations. Detailed descriptions of relevant methods are given in (Checkley et al., 2000; Singh et al., 2001; Kovats et al., 2004).

Estimating the effect of climate change on diarrhoeal incidence

Once the relationship between climate and diarrhoea is defined, the next step is to combine this with data from climate change scenarios to estimate per capita changes in future diarrhoeal rates. Projections of future temperature changes for selected scenarios and time points (see Section 2.3), relative to baseline conditions, can be imported into a GIS. The software can then be used to apply the relative risk per degree Celsius increase in temperature to the projected temperature increase, i.e. applying the relationship derived from the global study would give:

$$\text{Relative Risk} = 1.05^{(Ts-Tb)}$$

Where:

Ts = the mean temperature under the climate change scenario, and Tb is the mean temperature under baseline conditions.

The next step is to combine this with information on population distribution (see section 2.4) to estimate changes in human exposure. If the study population is a city or similar small geographic area (i.e. represented by a single grid cell or set of local meteorological data), then the relative risk calculated as above, for that single location, can be applied to the whole population. If the population covers a wider area (e.g., a large region or country), then the relative risks should be calculated separately for each grid cell, using GIS software functions. This map of relative risks can then be laid over grid maps of predicted population distributions, and the population in each grid cell multiplied by the corresponding relative risk. Summing together the values for the grid cells that cover the study population, and dividing by the total population, gives an estimate of the *per capita* relative risk in that study area.

As for other diseases, to estimate future disease burden (rather than proportional change from present) it is necessary to multiply this relative change by the diarrhoeal burden that would occur anyway in the absence of climate change. The options available are as for malaria, and consist of (i) assuming that the burden will remain as at present, (ii) using the future projections for diarrhoeal disease available at the WHO regional level (WHO, 2006a), or (iii) generating new projections of the effects of non-climatic variables specifically on diarrhoea in the population of interest. In the final case, the most important non-climatic influences that would need to be accounted for are likely to include the size and age structure of the population (diarrhoea burdens are greatest in very young children), the level of water and sanitation infrastructure, and the availability of basic health care.

Uncertainties in estimating impacts on diarrhoea

While there is a clear link between climate and diarrhoeal rates, there are considerable uncertainties associated with quantitative estimates of the effect of climate change. The most important are:

- As for other health impacts, estimates of the climate-disease relationship are usually derived from the results of short-term studies. Gradual changes to the climate may have more or less severe effects on diarrhoeal incidence.
- Assessments of the impact of climate change on diarrhoeal incidence that are based solely on temperature changes are likely to be underestimates. There is convincing evidence of the effect of extreme rainfall on waterborne outbreaks of diarrhoea, even in highly developed countries (Curriero et al., 2001). However, the association between rainfall and diarrhoeal incidence is far more complex than for temperature. In general, rainfall effects on diarrhoeal incidence (where observed) are non-linear. The findings from the few studies that have been conducted cannot easily be generalized to the total burden of diarrhoeal disease without information about the relative contribution of reported outbreaks to diarrhoeal incidence at the larger scale (i.e. country level).
- The few effect estimates of climate and diarrhoeal disease that have been calculated show reasonably similar effect sizes for the influence of temperature. Estimates of disease incidence could be more robust if studies were conducted in sites with a wider climatic and socio-economic spectrum. Site-to-site variations

in climatic conditions, pathogen mix and transmission routes may lead to local variations in the nature of the climate-disease relationship.

- Overall, estimates could be improved by an explicit investigation of the degree to which economic development and improved levels of development, water supply and sanitation influence vulnerability to the effect of climate variation on diarrhoeal disease.

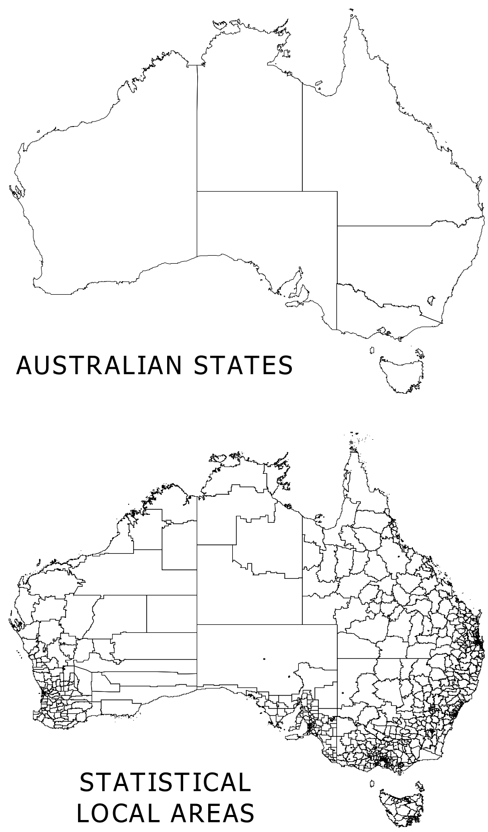
4. Estimating climate change impacts at a country level: worked examples from the Australasian assessment

4.1 General method

In 2003 the Australian government commissioned an assessment of climate change-related health risks (McMichael et al., 2003b). The assessment considered future health impacts for the years 2020 and 2050 for a number of health outcomes, with consideration of (i) the important public health issues for Australia, (ii) the sensitivity of different diseases to climate, (iii) the availability of quantitative methods for assessment, and (iv) the short timeframe within which the study was conducted.

The assessment adopted the IPCC range of future greenhouse gas emission scenarios, and used the B1, A1B and A1F1 scenarios to represent the range of uncertainty around future greenhouse gas emission levels. Two climate models were chosen to represent the spectrum of different precipitation projections: the CSIROMk2 and the ECHAM4.

Figure 5 Spatial boundaries used in different parts of the Australasian assessment: States and Statistical Local Areas.



The population projections were available for two time points and at two different spatial units:

- 2019, by Statistical Local Areas
- 2050, by State cities and "balance of State"

Both these population series were prepared by the Australian Bureau of Statistics. They were based on a number of assumptions about future fertility, mortality and migration rates. For the estimating dengue impacts, Statistical Local Area population data at both the study time points (i.e. 2020 and 2050) was needed. For estimating temperature impacts, city-level projections were required. For flood impact estimation, State level population projections were sufficient. The Statistical Local Area projections were estimated in the following manner. For 2020, a linear regression was used to extrapolate the population projections from 2010-2019 forward one year to 2020. For 2050 it was assumed that any changes in population size within a State would occur uniformly across all of the Statistical Local Areas. For example, if the total size of a capital city's population was projected to increase by 10% between 2019 and 2050, it was assumed that each Statistical Local Area within the city boundary would also increase in size by 10%. Similarly, if the balance of State population estimate decreased by 5% at 2050, then the population size of each regional Statistical Local Area in that state was reduced by 5%.

The following sections synthesize the methods used to estimate future change in populations at risk for each health outcome and present the results. The full methodological workings and implications of the findings can be read in the report (*Human Health and Climate Change in Oceania: A Risk Assessment, 2002*), which is available from the internet at
http://www.health.gov.au/pubhlth/publicat/document/metadata/env_climate.htm

4.2 Temperature-related deaths

The Australasian assessment estimated the temperature-related mortality in ten Australian and two New Zealand cities. Estimation was carried out at the city level, as there is greater evidence for effects of thermal extremes on urban mortality, temperature-health relationships are known to vary between cities in different climate zones, and the majority of policy responses to adapt to thermal extremes are likely to be carried out at the city rather than national level (Section 1). Here, we present the methods and results for the five largest Australian cities (Adelaide, Brisbane, Melbourne, Sydney, and Perth).

Method

Temperature-related deaths were estimated by building an exposure-response relationship from local daily temperature and death records for the city. Climate change projections were applied to estimate changes in temperature-related deaths out to the year 2050.

Baseline mortality estimate: A central health data collection agency for the country provided records of monthly all-cause mortality in people aged over 65 years from 1997 to 1999. Population data were obtained for the same period to establish baseline average annual mortality rates. The Australian standard classification of city boundaries was used to define the geographical extent of each city.

Exposure-response relationship at the baseline period: For each city, observations of daily maximum and minimum temperature were obtained for the years 1990 to 1999. The

Sydney, Melbourne and Adelaide data came from central city meteorological stations. The cities of Perth and Brisbane do not have continuous high-quality meteorological records from the central city area, and so data from airport stations were used instead (given the urban heat island effect, it is probable that the mortality for these two cities was underestimated). Table 8 presents the long-term average mean summer temperature profiles for these cities. Fortunately there were very few missing data: where this was the case, data were imputed from surrounding values. The frequency of days per degree Celsius (by month) across the ten years was tabulated. From this the average number of days of exposure to hazardous temperature in each city was calculated (i.e. the number of days above the hot threshold or below the cold threshold), weighted by degree of severity. The severity per degree Celsius above the threshold was determined by the temperature-mortality relationship for each city (a 3% increase in daily mortality per 1°C increase above a threshold of 28°C, described earlier). Finally, the daily risk metric was multiplied by the average mortality to give the incidence of mortality in the population attributable to extreme temperatures. The analysis did not account for the possible contribution of humidity to heat-related deaths in the sub-tropical city of Brisbane, which may mean the annual deaths in this city were underestimated.

Table 8 Average summer temperature profile during the baseline period (1990-1999)
Main cities in the Australasian climate change and health risk assessment

	Average Summer Temperatures*	
City	Mean max. (°C)	Days above 35°C
Adelaide	27	3.6
Brisbane	29	0.3
Melbourne	25.5	2.6
Perth	30.5	6.8
Sydney	25	0.7

Estimating future changes in mortality: Future maximum and minimum temperature projections were obtained for each city. The excess temperature-related mortality was calculated separately with and without adjustment for the projected changes in population size in the 65+ age group. The background mortality rate in the future was assumed to remain the same as in the baseline year (i.e. no change in health service delivery, physiological acclimatisation or behavioural adaptation to climate change).

Results

Extreme temperatures are estimated to cause 1100 deaths per year in people aged over 65years in the main Australian cities during the baseline period (1990-1999). The highest rate of deaths were in the cities of Perth and Adelaide (199/100 000 and 127/100 000 respectively) where maximum temperatures above 35°C are recorded occasionally during an average summer. The coastal temperate cities (e.g. Sydney) had the lowest rates – these cities have very few days above 35°C, on average. The annual number of temperature-related deaths from climate change is predicted to increase by 2050 to between 2400-3100. After adjusting for the increase in population size and ageing that is projected at that time, the excess mortality from heat in this older group is estimated to be 4240-6210 in an average year (Table 9). No cold-related deaths were expected to occur in these cities in the future. Figure 6 is a graphical representation of the results for these cities at 2050, showing the proportional contribution of the temperature and ageing effects.

As for the global assessment, there is no estimation of the numbers of *years* of life lost. Ideally, this should be calculated based on the difference in Years of Life Lost (YLL) from deaths due to thermal extremes under climate change, compared to YLL for deaths in thermal extremes under the counterfactual or "baseline" scenario. This calculation is complicated by the fact that some studies have shown that individuals who die in thermal extremes often have pre-existing health vulnerabilities, so that they have somewhat lower life expectancies than average for that age group; i.e. thermal extremes may hasten deaths by only a few months. However, the small amount of available research on this issue indicates that this "mortality displacement" effect is highly variable between sites, and between events (e.g. Hajat et al., 2005; Le Tertre et al., 2006; Kaiser et al., 2007). It is therefore not currently possible to generalize a "hastening period" for deaths in thermal extremes and to calculate attributable years of life lost in thermal extremes.

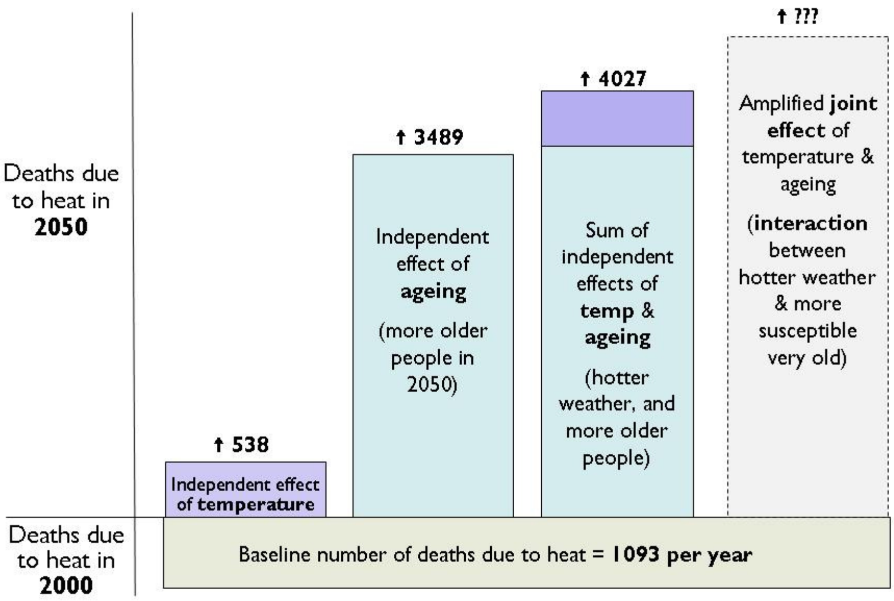
Table 9 Estimates of annual temperature-related deaths in people aged over 65 years for the baseline year (1999), 2020 and 2050*

	Average annual temperature-related mortality					
Capital City	**Baseline (1999)**		**2020**		**2050**	
	Deaths	Death rate (/100 000)	Deaths	Death rate (/100 000)	Deaths	Death rate (/100 000)
Adelaide	200	130	340 – 370	130 – 150	480 – 660	140 – 200
Brisbane	130	80	340 – 390	100 – 110	780 – 1370	120 – 200
Melbourne	290	70	570 – 600	80 – 90	980 – 1320	80 – 110
Perth	290	200	660 – 690	210 – 220	1250 – 1550	230 – 280
Sydney	180	40	360 – 400	40 – 50	750 – 1310	50 – 90

*The range of values in 2020 and 2050 incorporates the results of future greenhouse gas emission levels and climate model simulations of future temperatures. Future deaths are estimated after adjusting for the projected change in population size and ageing

Figure 6 Annual number of heat-related deaths due to temperature increase *per se* and ageing for the five largest Australian cities in 2050

Under the "mid" emissions scenario and the CSIROMk2 climate model



4.3 Risk of death from inland flooding

Method

The Australasian assessment used the same method as the global assessment, with slight modifications.

Exposure-response relationship: The baseline average monthly mean and variability of rainfall for each 0.25° grid cell in Australia was calculated using 10 years of observations (1961-1970). Projected grid cell monthly means for the future climate scenarios at 2020 and 2050 were used to estimate the change in frequency with which a '1 in 10 year (i.e., 1 in 120 month) event' would occur, using the formula described previously. The exposure risk results for each grid cell were averaged across Statistical Local Areas at the baseline period and for the two future periods. State level estimates (more useful for reporting and communication purposes than the much smaller Statistical Local Areas) were calculated using a weighted population average of the Statistical Local Area values.

Estimating the baseline death and injury rate from flooding: These rates were calculated by combining historical reports from the EM-DAT and Emergency Management Australia databases. Reported deaths and injuries from the two datasets were used to calculate national and State rates for the period 1970-2001 (98), based on relevant state and national population figures for the period. The average annual baseline death and injury incidence was calculated by dividing the average annual records of these outcomes over the 32 years by the mid-period state population (1985) (Table 10).

Table 10 Estimated deaths and injuries (cases and rates) from flooding in Australia, 1970 to 2001

State	Total		Average annual rate (per million)	
	Deaths	Injuries	Deaths	Injuries
New South Wales	97	336	0.57	1.98
Queensland	61	527	0.77	6.61
Northern Territory	14	40	3.04	8.69
South Australia	8	10	0.19	0.24
Australian Capital Territory	7	-	0.90	-
Western Australia	6	-	0.14	-
Victoria	6	46	0.05	0.36
Tasmania	1	15	0.07	1.09
Australia	**200**	**974**	**0.41**	**1.99**

Results

The risk of flood deaths and injuries was predicted to increase across most of Australia by 2020, with increases of 40-138% relative to baseline risk, depending on the State and the climate scenario (Table 11). Variation in flood risk within States (not shown) reflects the influence of topography, altitude, and coastal proximity on projected rainfall changes. In Queensland, pockets of the State were predicted to have a 200-385% increased risk of flooding. If global warming increases to the levels projected by the “high” emission scenarios, a few parts of Australia (southwest Western Australia and the populated areas of South Australia) are projected to have lower rainfall in future.

Table 11 Relative risk of death and injury due to flooding in 2020 for major Australian States

State	Relative Risk 2020	Relative Risk 2050
New South Wales	1.57 – 2.12	1.53 – 1.75
Victoria	1.41 – 2.38	1.17 – 1.49
Queensland	1.39 – 1.84	1.31 – 1.82
South Australia	0.97 – 1.37	0.78 – 0.91
Western Australia	0.97 – 1.25	0. 76 – 1.05
National	**1.39 – 1.97**	**1.29 – 1.48**

Relative risk = 1.0 for no change in risk; >1 = increase in risk; <1 = decrease in risk). The range of values represents result for the several climate models and exposure scenarios.

For the country as a whole, flood risk was predicted to increase by 39-97% around 2020. This translates to a predicted annual increase incidence of 5.7-8.1 deaths per 10 million people by 2020 (up from the baseline incidence of 4.1, see Table 12). Future reductions in rainfall for the country by 2050 provide a likely explanation for the predicted (small) decrease in flood risk at that time compared to 2020 (still a 29-48% increase from the baseline).

Table 12 Australian annual incidence of deaths and injuries due to flooding per million people
Baseline period (average from 1970-2001), and estimated for 2020 and 2050 [a,b]

Time	Deaths		Injuries	
	Rate (per million)	Number	Rate (per million)	Number
Baseline	0.41	7	1.99	31
2020	0.57 – 0.81	13-19	2.77 – 3.91	65-91
2050	0.53 – 0.61	14-16	2.56 – 2.95	68-78

[a] The range of values indicates alternative exposure scenarios and climate models.
[b] Population projections from the Australian Bureau of Statistics; the population projections for 2020 and 2050 are taken from the middle estimate

4.4 Dengue

Methods

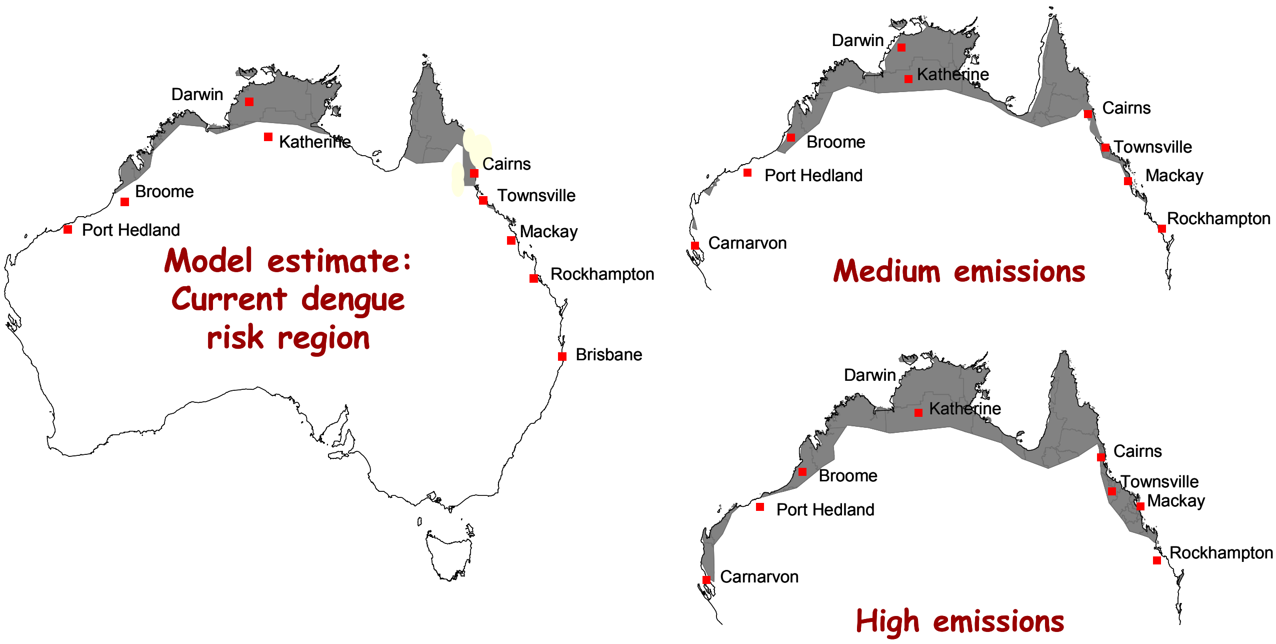
Incident cases of dengue (confirmed by pathology) are required to be reported to local health authorities in Australia. These data are collated into a national communicable disease surveillance system. The assessment used an empirical model developed by Hales and others (Hales et al., 2002) to estimate the future number of people living in a region that would be climatically suitable for dengue transmission. This model was a regression of climate on the reported distribution of dengue epidemics, world-wide, during the period 1975 to 1996 (cell size 0·5° latitude and longitude). The climatic variable which best predicted dengue epidemics was annual average vapour pressure (calculated using data from the period 1961-1990). The output of the model was a number between 0 and 1, which represented the probability that one or more epidemics of dengue fever would have occurred in a given area under baseline climate conditions. Based on humidity alone, the model had an accuracy of 89% in predicting where dengue epidemics had occurred historically.

The regression coefficients for the Hales model were obtained from the author. The estimated vapour pressure values for Australia (at the baseline period and for 2020 and 2050) at a cell size of 0.25^{o} (approximately 25 km^2) were exported from a GIS and converted into a single column of data. These were transferred into a statistical package format (Stata). Applying the regression coefficients to the Australian vapour pressure values provided an output that was the probability of the risk of dengue transmission (between zero and one) for each grid cell in Australia. These data were imported into a GIS as a text file with a standard ASCII header and one row per grid cell. Areas where the model estimated the probability of transmission as greater than 0.5 (50%) were coded as "at risk" of dengue. Maps of Australian local administrative boundaries and of population were overlaid onto each of the dengue distribution scenarios, and the baseline and future populations at risk were calculated.

Results

Climate change is likely to increase the area of land with a climate suitable for dengue fever transmission in Australia, and an increased number of people are expected to be living in the dengue risk region (Figure 7). Projected population change is accounted for in the future estimates. The modelling does *not* account for the possibility of adaptive strategies, which would be likely to reduce the risk of transmission in these regions.

Figure 7 Estimated population at risk of dengue transmission under baseline climate conditions (A) and in 2050 (B)*



Results of a logistic regression model with vapour pressure (humidity) as the predictor of dengue fever risk (Hales et al., 2002)

The different methods used to assess the future risk of dengue and malaria in Australia highlight the context-specific nature of burden of disease assessments. Although both diseases have a human host and a mosquito vector, several factors combine to make dengue a greater public health threat than malaria in the *Australian* context. First, there is more potential for dengue outbreaks to spread rapidly within the population. Effective, fast-acting treatments are available for malaria that kill the parasite, and people with malaria remain infectious for a much shorter period (in contrast, no treatments are available to reduce the period of viraemia with dengue). Second, the dengue mosquito prefers to breed in the urban environment and to feed on humans. Prevention of infection requires continual attention to clearing or treating domestic containers that hold water (such as buckets, pot plant bases and tyres), and infrastructure (such as sumps and telecommunication pits), and to applying mosquito repellent during outbreaks. Conversely, the malaria mosquito does not have a preference for breeding in urban environments, and bed nets provide a simple and effective form of protection. For these several reasons, the risk of infection and the complexity of prevention and control are higher for dengue than for malaria in Australia.

Uncertainty

- This model (Hales et al., 2002) does not have a high level of temporal precision. It classifies regions as being at risk of at least one epidemic of dengue in a year (i.e. climatic conditions at some point throughout a year are suitable for maintaining the dengue vector). It is not able to give information about the *duration* or *timing* of the dengue transmission season across the year. An indication of the number of risk months would be useful for estimating risk management activities and their cost.
- The model treats geographical units equally, without reference to the role of population density within a region in increasing transmission risk.

4.5 Malaria

Methods

The available malaria models at either global or continental resolution may not be relevant within specific countries, either due to coarse spatial resolution, or inappropriateness of applying biological relationships derived in one region (e.g. Africa), to the very different vector and human ecology in other regions. The Australasian assessment was able to use a software program (CLIMEX, Sutherst 2004) based on observations of mosquito species in Australia. CLIMEX produces a probability index of mosquito distribution (in this case *An. farauti s.l*) in response to varying climate conditions. The model uses hydrological principles to calculate a soil moisture index which, combined with temperature, estimate likely mosquito population growth. A series of stress indices estimate the threat to a species of prolonged periods of excessively cold, hot, dry or wet conditions. The combination of these inputs represents the climatic suitability of locations for the permanent survival and propagation of the malaria transmitting species *An. farauti s.l.*

The assessment also considered the distribution of the two most significant species of malaria parasites (*Plasmodium vivax* and *P. falciparum*). For malaria transmission to occur, climatic conditions must be suitable for both vector breeding and parasite development and replication. *P. vivax* has a developmental threshold temperature of around 14-16°C, lower than that for *P. falciparum* (16-19°C, Martens et al., 1999). The values of 15°C and 18°C were used as the temperature thresholds for *P. vivax* and *P. falciparum* respectively in the assessment. The modelling considered the current distribution of *Plasmodium*, and estimated potential distribution with an increase of 3°C in temperatures.

Software incompatibilities prevented the use of the same climate data for the malaria estimates as was used for the other health outcome estimates in the Australasian assessment. The climate surface from the Climate Research Unit in Norwich, UK was used. This surface has a grid cell size of about 55 km^2, about twice that used for the rest of the assessment. Due to the additional averaging (especially of coastal plains in some areas), the results are necessarily less precise than those for the dengue analysis. The modelling used a different range of future temperature and rainfall scenarios to the SRES that were used for the rest of the assessment. Future changes in climate were constrained within the range projected by the CSIROMk2 climate model for each time point (i.e. 1-3°C for temperature and -40 to +20% for rainfall).

Results

Limits to the development of the malaria parasites

The model results indicate that both species of malaria could develop for several months over summer in most areas of Australia (conditional on a suitable vector being present). Temperatures were most suitable for *P. falciparum* in the tropical north and for *P. vivax* in the temperate areas to the south of the continent. Under a temperature increase of 3°C above baseline a noticeable southward shift of both species was projected, with declines in inland and north-western regions due to excessive heat.

Distribution of the malaria vector (results for 2050 only)

1. Change in temperature, no change in rainfall
Increasing temperatures are estimated to progressively extend the southern distribution of *An. farauti s.l.* from Mackay to the Bundaberg area (just north of Brisbane), while also making that belt of coast and hinterland more suitable. The mosquito may also be able to colonize further inland in the southern area.

2. Warmer (1.0 – 3°C) and wetter (+ 20% rainfall)
As above, with a much more significant potential colonization of the mosquito into the coastal hinterland regions.

3. Warmer (1.0 – 3°C) and drier (- 40% rainfall)
As above, however given the extreme reduction in rainfall the transmission zone would be strictly confined to the coast and islands.

4.6 Diarrhoeal disease

The most important pathogenic agents of diarrhoeal diseases in developed countries have been classified as: bacterial (*Campylobacter, Salmonella, E. coli,* and *Shigella*), viral (C*alicivirus, Rotavirus*), and parasitic (*Cryptosporidium, Giardia*) (Tauxe and Cohen, 1995). Gastrointestinal infections due to these organisms are transmitted from person-to-person (faecal-oral route, or respiratory), animal-to-person, or are food-borne or water-borne. Food-borne transmission is estimated to account for 35% of all diarrhoeal cases in the United States (Mead et al., 1999). In Australia, an estimated 2-4 million cases of food-borne infectious disease occur annually (ANZFA, 1999).

Methods

Estimation of baseline incidence rate: The Northern Territory Health Department provided records of all diarrhoeal admissions to the Alice Springs hospital for children under 10 years of age from 1996-2002 (Aboriginal status of the child was recorded). The Alice Springs hospital receives patients from a very large catchment area (west into the Gibson Desert and to communities on the edge of the Simpson Desert). The Alice Springs Health Region boundary was used to approximate this region, and obtained annual temperature and rainfall averages for future time points and alternative emission scenarios. An incidence rate could not be estimated for this region due to the lack of an available denominator population. In addition to the unknown true extent of the Alice Springs hospital catchment area, estimating population numbers for remote Aboriginal settlements is extremely difficult due to the constant movement of people between settlements. Therefore the assessment could only estimate the baseline level of severe diarrhoeal disease among Aboriginal people in central Australia, and of the likely increase in diarrhoeal hospital admissions in future – given projected changes in temperatures. It does not account for changes in population size or distribution in future, changes in infrastructure (such as improvements to housing and water supply), changes in diarrhoeal interventions, etc.

Exposure-response relationship: At the time of the Australasian assessment a climate-diarrhoeal incidence estimate had only been calculated for developing countries (Peru and Fiji, discussed previously). Given the availability of sanitation infrastructure, education, and high quality housing in most of Australia it was not appropriate to apply the results of these studies to estimate future risk for the general Australian population. However, living conditions and access to services in many remote Aboriginal communities of Australia are poor. Rates of salmonellosis are much higher in the Northern Territory and northern Western Australia where remote Aboriginal populations comprise a far higher proportion of the total State populations than in eastern Australia (Roche et al., 2001). It was considered reasonable to compare the living conditions of Aborigines in remote areas to those of many people living in developing nations.

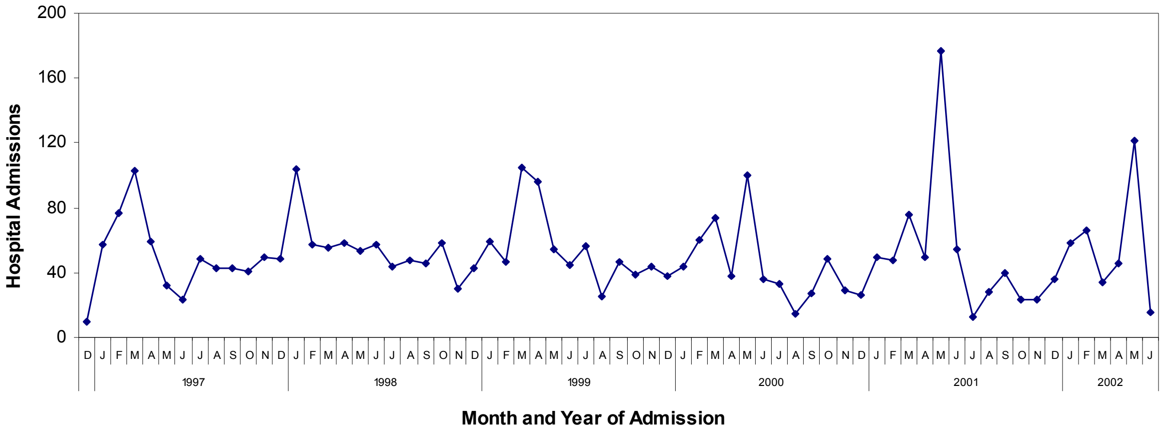
The assessment examined the impact of increasing temperatures on the incidence of severe all-cause diarrhoea (specifically hospital admissions) of Aborigines living in central Australia. The mid-point estimate of the Fiji and Peru studies was used to provide the exposure-response relationship. That is, a 5% increase in risk of severe diarrhoea was assumed for each 1°C increase in predicted future temperatures. Relative risks were calculated by multiplying the projected increase in temperature by the exposure-response value. The resulting increase in relative risk was multiplied with the baseline annual diarrhoeal admission estimate to provide an estimate of the possible future numbers of admissions.

Results

There were 3824 children hospitalized with diarrhoea at the Alice Springs hospital between 1996 and 2002 (an average of 624 per year). Of these children, 90% were Aboriginal. Most (79%) were less than two years old. There was a seasonal pattern to admissions, with a peak between March and May (Figure 8) and lowest numbers between

June and December in most years. Average monthly temperatures for the region are typically highest from December to February (28°C), and lowest from June to August (13°C).

Figure 8 Monthly time-series of Aboriginal children (< 10 years) hospitalized with diarrhoea at the Alice Springs hospital, 1996 to 2002



The mean annual temperature for this region is projected to increase 0.5-1.0°C by 2020 and 1.0-3.5°C by 2050. This could translate to an increase of 3-5% in diarrhoeal admissions by 2020, and of 5-18% by 2050, relative to the baseline. Thus, diarrhoeal hospitalisations in Aboriginal children under 10 years old in this area may increase to between 660 and 730 by 2050. This is likely to be conservative, as natural growth appears to be higher for Aboriginal Australians than it does for the total Australian population. In addition, growth patterns vary regionally, and the fertility rate for Aborigines in Central Australia has been higher than for elsewhere. The baseline incidence (independent of climate change) would vary over time, and could be expected to decrease with economic development and improvements to sanitation and hygiene.

5. Discussion and policy relevance of estimates

The quantitative environmental burden of disease approach outlined here has a series of particular characteristics, which make it a useful complement to both specific studies, and general frameworks to assess health threats from climate change (Kovats et al., 2003). First, by aiming at a comprehensive assessment, it gives a better representation of the health consequences of climate change than studies of single disease outcomes in restricted populations. Secondly, the quantitative approach helps to identify the relative public health burden of different climate-sensitive diseases in different populations. The global assessment, for example, showed that relatively small proportional increases in risk for climate sensitive diseases such as diarrhoea and malnutrition may cause very large increases in the total future disease burden. It also helped to demonstrate that the health risks of climate change fall mainly children in developing countries, who have contributed least to the emissions of greenhouse gases that cause climate change (Patz et al., 2005). It therefore emphasizes the need for shared international responsibility for protecting health under a changing climate.

The attempt to carry out a full accounting of the health impacts of climate change rapidly clarifies important gaps in our current knowledge. Most of the climate-health models estimate the effects of changing mean values of a climate condition, usually temperature, whereas there is increasing evidence that less predictable changes in extreme values, especially precipitation, may be more important for many diseases. The outputs of many models relevant to such assessments (e.g. predictions of changes in the land area suitable for malaria transmission, (Thomas et al., 2004); population exposed to malaria, (Rogers and Randolph, 2000); or per-capita duration of exposure (Tanser et al., 2003), are only indirectly linked to disease rates, and are therefore represent only very approximate measures of impacts on the burden of clinical disease. Finally, many plausible or even probable mechanisms by which climate change may impact on health have not been modelled quantitatively, and have therefore not been included in these assessments. These include low probability but high-impact outcomes, such as positive feedbacks from greenhouse gases leading to rapidly accelerating climate change. Future research should assess the health risks – and adaptive requirements – that an abrupt climate change might provoke.

In presenting these findings to decision-makers it is therefore important to make clear the limitations of these assessments: quantitative estimates are unavoidably uncertain; changes in non-climatic factors will influence both the baseline rates of disease and their sensitivity to climate effects; and many of the mechanisms by which climate change may affect health are not currently modeled, more likely leading to an underestimation rather than an overestimation of health threats.

The necessary next step is to use such assessments to plan interventions to protect health under a chaning climate. This is now beginning to occur, as countries begin to assess their disease risks, and to plan and implement adaptive interventions (WHO, 2006b). The quantitative assessments described here sould therefore form just one component in an ongoing process of risk assessment, intervention, evaluation and refinement of responses, to deal with what is now increasingly recognized as a serious public health issue.

Annex Summary results of the global assessment of the disease burden from climate change

The approach used in this guide to assess the burden of disease from climate change is based on that used in the global analysis of the disease burden (WHO, 2002; McMichael et al., 2004). The global analysis covered the 14 WHO sub regions of the world (Table A1) in the year 2000.

Table A1 Country groupings for the WHO sub regions in the Global Burden of Disease assessment[a]

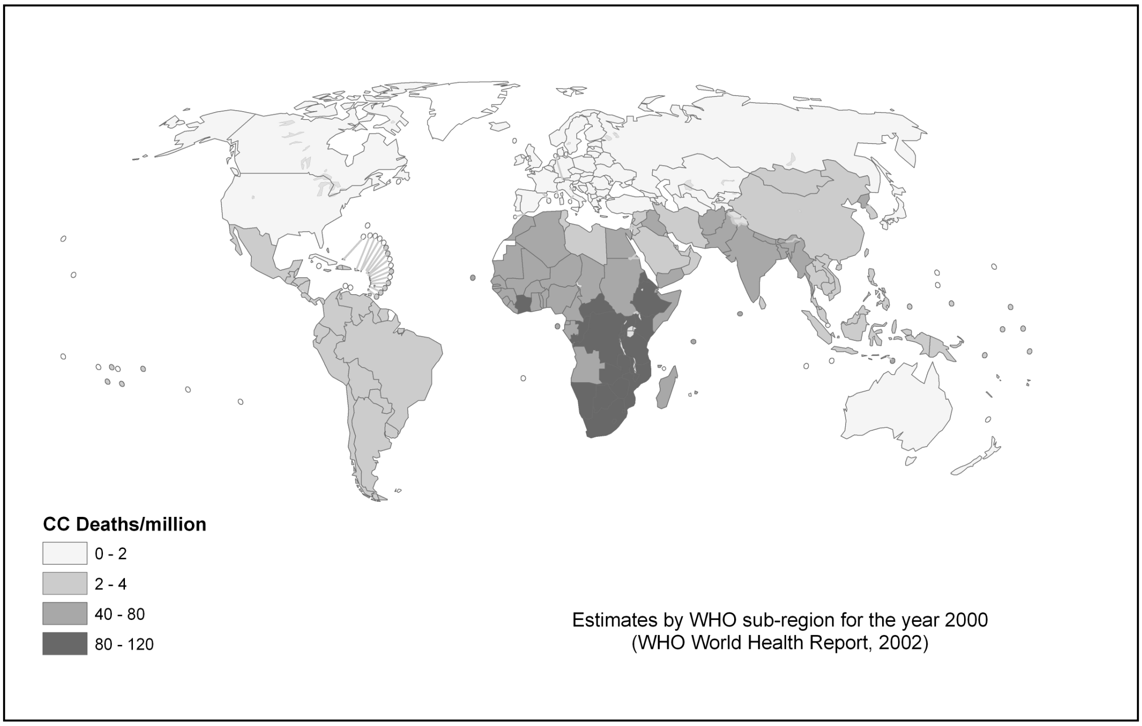
Subregion[b]		WHO Member States
AFR	D	Algeria, Angola, Benin, Burkina Faso, Cameroon, Cape Verde, Chad, Comoros, Equatorial Guinea, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Madagascar, Mali, Mauritania, Mauritius, Niger, Nigeria, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Togo.
AFR	E	Botswana, Burundi, Central African Republic, Congo, Côte d'Ivoire, Democratic Republic of the Congo, Eritrea, Ethiopia, Kenya, Lesotho, Malawi, Mozambique, Namibia, Rwanda, South Africa, Swaziland, Uganda, United Republic of Tanzania, Zambia, Zimbabwe.
AMR	A	Canada, Cuba, United States of America.
AMR	B	Antigua and Barbuda, Argentina, Bahamas, Barbados, Belize, Brazil, Chile, Colombia, Costa Rica, Dominica, Dominican Republic, El Salvador, Grenada, Guyana, Honduras, Jamaica, Mexico, Panama, Paraguay, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, Uruguay, Venezuela.
AMR	D	Bolivia, Ecuador, Guatemala, Haiti, Nicaragua, Peru.
EMR	B	Bahrain, Cyprus, Iran (Islamic Republic of), Jordan, Kuwait, Lebanon, Libyan Arab Jamahiriya, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, Tunisia, United Arab Emirates.
EMR	D	Afghanistan, Djibouti, Egypt, Iraq, Morocco, Pakistan, Somalia, Sudan, Yemen.
EUR	A	Andorra, Austria, Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Slovenia, Spain, Sweden, Switzerland, United Kingdom.
EUR	B	Albania, Armenia, Azerbaijan, Bosnia and Herzegovina, Bulgaria, Georgia, Kyrgyzstan, Poland, Romania, Slovakia, Tajikistan, The Former Yugoslav Republic of Macedonia, Turkey, Turkmenistan, Uzbekistan, Yugoslavia.
EUR	C	Belarus, Estonia, Hungary, Kazakhstan, Latvia, Lithuania, Republic of Moldova, Russian Federation, Ukraine.
SEAR	B	Indonesia, Sri Lanka, Thailand.
SEAR	D	Bangladesh, Bhutan, Democratic People's Republic of Korea, India, Maldives, Myanmar, Nepal, Timor Leste.
WPR	A	Australia, Brunei Darussalam, Japan, New Zealand, Singapore.
WPR	B	Cambodia, China, Cook Islands, Fiji, Kiribati, Lao People's Democratic Republic, Malaysia, Marshall Islands, Micronesia (Federated States of), Mongolia, Nauru, Niue, Palau, Papua New Guinea, Philippines, Republic of Korea, Samoa, Solomon Islands, Tonga, Tuvalu, Vanuatu, Viet Nam

[a] Source: WHO (2003); status in the year 2003

[b] Sub regions: AFR = Africa; AMR = Americas; EMR = Eastern Mediterranean; EUR = Europe; SEAR = South-East Asia; WPR = Western Pacific; A: Very low child, very low adult mortality; B: Low child, low adult mortality; C: Low child, high adult mortality; D: High child, high adult mortality; E: High child, very high adult mortality.

At the time of the global assessment, estimates of burdens of specific diseases were available only for the year 2000. Future projections of what was likely to happen to these burdens in the absence of climate change were generated only much later (Mathers and Loncar, 2006). The assessment therefore reported estimated relative risks (i.e. proportional changes) in disease risks for years out to 2030, but reported estimates of disease burdens from climate change only for the year 2000. These are summarized in Figure A1, and Tables A2 and A3.

Figure A1 Estimated deaths per million people attributable to climate change in the year 2000 by subregion



NB: This is only a schematic representation. The boundaries and names shown and the designations used on this map do not imply the expression of any opinion whatsoever on the part of the World Health Organization concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries.

Table A2 Estimated mortality in thousands attributable to climate change in the year 2000 by cause and subregion

Subregion	Malnutrition	Diarrhoea	Malaria	Floods	CVD	All causes	Total deaths/million population
AFR-D	8	5	5	0	1	19	66.83
AFR-E	9	8	18	0	1	36	109.40
AMR-A	0	0	0	0	0	0	0.15
AMR-B	0	0	0	1	1	2	3.74
AMR-D	0	1	0	0	0	1	10.28
EMR-B	0	0	0	0	0	1	5.65
EMR-D	9	8	3	1	1	21	61.30
EUR-A	0	0	0	0	0	0	0.07
EUR-B	0	0	0	0	0	0	1.04
EUR-C	0	0	0	0	0	0	0.29
SEAR-B	0	1	0	0	1	2	7.91
SEAR-D	52	22	0	0	7	80	65.79
WPR-A	0	0	0	0	0	0	0.09
WPR-B	0	2	1	0	0	3	2.16
World	*77*	*47*	*27*	*2*	*12*	*166*	*27.82*

CVD, cardiovascular disease.

Table A3 Estimated disease burden in 000s of DALYs attributable to climate change in the year 2000 by cause and sub region

Subregion	Malnutrition	Diarrhoea	Malaria	Floods	All causes	Total DALYs/million population
AFR-D	293	154	178	1	626	2 185.78
AFR-E	323	260	682	3	1 267	3 839.58
AMR-A	0	0	0	4	4	11.85
AMR-B	0	0	3	67	71	166.62
AMR-D	0	17	0	5	23	324.15
EMR-B	0	14	0	6	20	147.57
EMR-D	313	277	112	46	748	2 145.91
EUR-A	0	0	0	3	3	6.66
EUR-B	0	6	0	4	10	48.13
EUR-C	0	3	0	1	4	14.93
SEAR-B	0	28	0	6	34	117.19
SEAR-D	1 918	612	0	8	2 538	2 080.84
WPR-A	0	0	0	1	1	8.69
WPR-B	0	89	43	37	169	111.36
World	*2 846*	*1 459*	*1 018*	*193*	*5 517*	*925.35*

The assessment therefore concluded that the climate change that has occurred since the period 1961-1990 may already have caused over 150,000 deaths[1], or the loss of over 5.5 million disability adjusted life years, annually, by the year 2000.

The various causes considered here differed markedly in their contribution to the estimates of the overall burden of disease. Climate-change effects on malnutrition, diarrhoea and vector-borne diseases appeared considerably more important than effects on flooding, or on deaths attributable to thermal extremes. There is also marked regional variations. Estimated DALY burdens per capita are several hundred times greater in the poorer regions of Africa, parts of the Eastern Mediterranean region and South-East Asia than in Western Europe, North America, and the more developed regions of the Western Pacific. This is largely a reflection of the much higher baseline incidence of the most important climate-sensitive diseases (malaria, diarrhoea and malnutrition) in these poorer regions, but also of greater vulnerability to climate change effects. These major climate-sensitive diseases mainly affect younger age groups. Health burdens from climate change appear to be borne mainly by children in developing countries.

[1] The summary estimate in the table is higher (166,000). However, this includes an estimated 12,000 deaths from CVD in thermal extremes in regions that are estimated to experience net increases in such deaths - but does not include estimated net decreases in other regions. For this reason we refer to the more conservative and approximate estimate of "over 150,000 deaths".

References

Alderson, M.R., (1985). Season and mortality. *Health Trends*, 17: 87-96.

ANZFA, (1999). *Food Safety Standards Costs and Benefits*, Canberra, Australia and New Zealand Food Authority.

Blaser, M.J., Smith, P.D., Ravdin, J.I., Greenberg, H.B. and Guerrant, R.I. (Editors), (1995). *Infections of the gastrointestinal tract*. Raven Press, New York.

Bouma, M.J., Kovats, R.S., Goubet, S.A., Cox, J.S.H. and Haines, A., (1997). Global assessment of El Nino's disaster burden. *Lancet*, 350(9089): 1435-1438.

Braga, A.L., Zanobetti, A. and Schwartz, J., (2001). The time course of weather-related deaths. *Epidemiology*, 12(6): 662-7.

Braga, A.L., Zanobetti, A. and Schwartz, J., (2002). The effect of weather on respiratory and cardiovascular deaths in 12 U.S. cities. *Environ Health Perspect*, 110(9): 859-63.

Checkley, W. et al., (2000). Effects of El Nino and ambient temperature on hospital admissions for diarrhoeal diseases in Peruvian children. *Lancet*, 355(9202): 442-450.

Christophers, R.S., (1911). *Malaria in the Punjab: Scientific Memoirs by Officers of the Medical and Sanitary Department of the Government or India*, Medical and Sanitary Department of the Government or India.

Coates, L., (1999). Flood fatalities in Australia, 1788-1996. *Australian Geographer*, 30(3): 391-408.

Coleman, P.G., Perry, B.D. and Woolhouse, M.E.J., (2001). Endemic stability - a veterinary idea applied to human public health. *Lancet*, 357: 1284-1286.

Craig, M.H., Snow, R.W. and le Sueur, D., (1999). A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitology Today*, 15(3): 105-111.

Crowley, T.J., (2000). Causes of climate change over the past 1000 years. *Science*, 289(5477): 270-277.

CRU, (2006). *Climatic Research Unit: Global Climate Dataset 1901-2000* http://ipcc-ddc.cru.uea.ac.uk/obs/cru_climatologies.html.

CSIRO, (2001). *Climate Change Projections for Australia*, Melbourne: Climate Impact Group, CSIRO Division of Atmospheric Research.

Curriero, F.C., Patz, J.A., Rose, J.B. and Lele, S., (2001). The association between extreme precipitation and waterborne disease outbreaks in the United States, 1948-1994. *American Journal of Public Health*, 91(8): 1194-1199.

Drasar, B.S., Tomkins, A.M. and Feacham, R.G., (1978). *Seasonal aspects of diarrhoeal disease*. In: R.G. Feacham (Editor), Seasonal dimensions to rural poverty, University of Sussex

Dye, C., (1992). The analysis of parasite transmission by bloodsucking insects. *Annu Rev Entomol*, 37: 1-19.

Emergency Management Australia, (2006). *Emergency Management Australia Disasters Database* http://www.ema.gov.au/ema/emaDisasters.nsf.

Epstein, P.R., (1999). Climate and health. *Science*, 285: 347-348.

Ezzati, M., Lopez, A., Rodgers, A. and Murray, C. (Editors), (2004). *Comparative Quantification of Health Risks: Global and Regional Burden of Disease due to Selected Major Risk Factors.* World Health Organization, Geneva.

Garrett-Jones, (1964). The human blood index of malaria vectors in relation to epidemiological assessment. *Bulletin of the Worl Health Organization*, 31: 241-261.

Gouveia, N., Hajat, S. and Armstrong, B., (2003). Socio-economic differentials in the temperature-mortality relationship in São Paulo, Brazil. *International Journal of Epidemiology*, in press.

Green, M.S., Harari, G. and Kristal-Boneh, E., (1994). Excess winter-mortality from ischaemic heart disease and stroke during colder and warmer years in Israel. *European Journal of Public Health*, 4: 3-11.

Hajat, S. and Haines, A., (2002). Associations of cold temperatures with GP consultations for respiratory and cardiovascular disease amongst the elderly in London. *Int J Epidemiol*, 31(4): 825-30.

Hajat, S. et al., (2001). Association between air pollution and daily consultations with general practitioners for allergic rhinitis in London, United Kingdom. *American Journal of Epidemiology*, 153(7): 704-714.

Hajat, S., Armstrong, B.G., Gouveia, N. and Wilkinson, P., (2005). Mortality displacement of heat-related deaths: a comparison of Delhi, São Paulo, and London. *Epidemiology*, 16(5): 613-20.

Hales, S., de Wet, N., Maindonald, J. and Woodward, A., (2002). Potential effect of population and climate changes on global distribution of dengue fever: an empirical model. *Lancet*, 360(9336): 830-4.

Hay, S.I., Tatem, A.J., Guerra, C.A. and Snow, R.W., (2006). *Foresight on population at malaria risk in Africa: 2005, 2015 and 2030. Scenario review paper prepared for the Detection and Identification of Infectious Diseases Project (DIID), Foresight Project, Office of Science and Innovation.*, London, UK.

Hoozemans, F.M.J. and Hulsburgen, C.H., 1995. *Sea-level rise: a worldwide assessment of risk and protection costs.* In: D. Eisma (Editor), Climate Change: Impact on Coastal Habitation. Lewis Publishers, London, pp. 137-163.

Hutchinson, M.F., Nix, H.A., McMahon, J.P. and Ord, K.D., (1996). *The development of a topographic and climate database for Africa* http://www.ncgia.ucsb.edu/conf/SANTA_FE_CD-ROM/sf_papers/hutchinson_michael_africa/africa.html.

IFRC, (2005). *World Disaster Report 2005*. Oxford University Press, Oxford, United Kingdom and New York, NY, USA.

IMAGE Team, (2002). *The IMAGE 2.2 implementation of the SRES scenarios*. RIVM Bilthoven

IPCC, (1996). *Climate Change 1995. The Science of Climate change.* In: J.T. Houghton and e. al. (Editors), Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, New York.

IPCC, (2001a). *Climate Change 2001: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Third assessment Report*. Cambridge University Press, Cambridge, 1032 pp.

IPCC, (2001b). *Climate Change 2001: The Scientific Basis: Contribution of Working Group I to the Third Assessment Report*. Cambridge University Press, Cambridge.

IPCC Data Distribution Centre, (2006). *Socio-Economic Data and Scenarios* http://sedac.ciesin.columbia.edu/ddc/sres/index.html.

ISOTHURM, (2002). ISOTHURM STUDY GROUP: International study of temperature and heatwaves on urban mortality in low and middle income countries. *Lancet*, submitted.

Jetten, T.H., Martens, W.J.M. and Takken, W., (1996). Model simulations to estimate malaria risk under climate change. *Journal of Medical Entomology*, 33(3): 361-371.

Jovel, J.R., (1989). *Natural disasters and their economic and social impact*. CEPAL Review No. 38, Economic Commissions, Latin America and the Caribbean, Santiago, Chile.

Kaiser, R. et al., (2007). The Effect of the 1995 Heat Wave in Chicago on All-Cause and Cause-Specific Mortality. *Am J Public Health*, 97:S158–S162.

Karl, T.R. and Knight, R.W., (1998). Secular trends of precipitation amount, frequency, and intensity in the United States. *Bulletin of the American Meteorological Society*, 79(2): 231-241.

Keatinge, W.R., (1984). Physiopathology of the Cardiovascular-System - Alpert,Js. *Lancet*, 1(8391): 1386-1386.

Knutson, T.R. and Tuleya, R.E., (2004). Impact of CO2-Induced Warming on Simulated Hurricane Intensity and Precipitation: Sensitivity to the Choice of Climate Model and Convective Parameterization. *Journal of Climate*, 17(18): 3577-3495.

Kosatsky, T., (2005). The 2003 European heat waves. *Euro Surveill*, 10(7).

Kovats, R., Menne, B. and Ebi, K., (2003). *Methods of assessing human health vulnerability and public health adaptation to climate change*, WHO-European Centre for Environment and Health, Rome.

Kovats, R.S., Bouma, M.J. and Haines, A., (1999). *El Nino and Health*. WHO/SDE/PHE/99.4, World Health Organization.

Kovats, R.S., Campbell-Lendrum, D.H., Reid, C. and Martens, P., (2000). *Climate and vector-borne disease: An assessment of the role of climate in changing disease patterns*, United Nations Environment Programme.

Kovats, R.S. et al., (2004). The effect of temperature on food poisoning: a time-series analysis of salmonellosis in ten European countries. *Epidemiol Infect*, 132(3): 443-53.

Kuhn, K.G., Campbell-Lendrum, D.H., Armstrong, B. and Davies, C.R., (2003). Malaria in Britain: past, present, and future. *Proc Natl Acad Sci U S A*, 100(17): 9997-10001.

Kundzewicz, Z.W. and Kaczmarek, Z., (2000). Coping with hydrological extremes. *Water International*, 25(1): 66-75.

Kunst, A., Looman, C. and Mackenbach, J., (1993). Outdoor air temperature and mortailty in the Netherlands - a time series analysis. *American Journal of Epidemiology*, 137(3): 331-341.

Last, J.M., (2001). *A Dictionary of Epidemiology*. Oxford University Press, New York.

Le Tertre, A. et al., (2006). Impact of the 2003 heatwave on all-cause mortality in 9 French cities. *Epidemiology*, 17(1): 75-9.

MacDonald, G., (1957). *The Epidemiology and Control of Malaria*. Oxford University Press, London.

Martens, P. et al., (1999). Climate change and future populations at risk of malaria. *Global Environmental Change-Human and Policy Dimensions*, 9: S89-S107.

Martens, W.J., Jetten, T.H., Rotmans, J. and Niessen, L.W., (1995a). Climate change and vector-borne diseases: a global modelling perspective. *Global Environmental Change*, 5 (3): 195-209.

Martens, W.J., Niessen, L.W., Rotmans, J., Jetten, T.H. and McMichael, A.J., (1995b). Potential impact of global climate change on malaria risk. *Environmental Health Perspectives*, 103(5): 458-464.

Martens, W.J.M., (1998). Health impacts of climate change and ozone depletion: An ecoepidemiologic modeling approach. *Environmental Health Perspectives*, 106: 241-251.

Martin, P.H. and Lefebvre, M.G., (1995). Malaria and Climate - Sensitivity of Malaria Potential Transmission to Climate. *Ambio*, 24(4): 200-207.

Mason, S.J., Waylen, P.R., Mimmack, G.M., Rajaratnam, B. and Harrison, J.M., (1999). Changes in extreme rainfall events in South Africa. *Climatic Change*, 41(2): 249-257.

Massad, E. and Forattini, O.P., (1998). Modelling the temperature sensitivity of some physiological parameters of epidemiologic significance. *Ecosystem Health*, 4(2): 119-129.

Mathers, C. and Loncar, D., (2006). Projections of global mortality and burden of disease from 2002 to 2030. *PLoS Med*, 3 (11):e442.

McMichael, A. et al., 2004. *Climate Change*. In: M. Ezzati, A. Lopez, A. Rodgers and C. Murray (Editors), Comparative Quantification of Health Risks: Global and Regional Burden of Disease due to Selected Major Risk Factors. World Health Organization, Geneva.

McMichael, A. et al. (Editors), (2003a). *Climate Change and Human Health: Risks and Responses*. WHO, Geneva.

McMichael, A. et al., (2003b). *Human health and climate change in Oceania: a risk assessment*, Commonwealth of Australia, Canberra.

McMichael, A.J., Woodruff, R.E. and Hales, S., (2006). Climate change and human health: present and future risks. *Lancet*, 367(9513): 859-69.

Mead, P.S. et al., (1999). Food-related illness and death in the United States. *Emerg Infect Dis*, 5(5): 607-25.

Menne, B., Pond, K., Noji, E.K. and Bertollini, R., (1999). *Floods and Public Health Consequences, Prevention and Control Measures.* UNCE/MP.WAT/SEM.2/1999/22, WHO European Centre for Environment and Health, Rome, Italy.

Milly, P.C.D., Wetherald, R.T., Dunne, K.A. and Delworth, T.L., (2002). Increasing risk of great floods in a changing climate. *Nature*, 415(6871): 514-517.

Mouchet, J. and Manguin, S., (1999). Global warming and malaria expansion. *Annales De La Societe Entomologique De France*, 35: 549-555.

Nakicenovic, N.E.A., (2000). *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, U.K., 599 pp.

NASA, (2006). *Goddard Institute for Space Studies: Surface Temperature Analysis: Analysis Graphs and Plots*. NASA: GISS http://data.giss.nasa.gov/gistemp/graphs/.

New, M., Hulme, M. and Jones, P., (1999). Representing twentieth-century space-time climate variability. Part I: Development of a 1961-90 mean monthly terrestrial climatology. *Journal of Climate*, 12(3): 829-856.

Nicholls, R.J., Hoozemans, F.M.J. and Marchand, M., (1999). Increasing flood risk and wetland losses due to global sea- level rise: regional and global analyses. *Global Environmental Change-Human and Policy Dimensions*, 9: S69-S87.

Noji, E.K., (1997). *The public health consequences of disasters*. Oxford University Press, New York, 468 pp.

OFDA/CRED, (2006). *EM-DAT: The International Disaster Database*. Université Catholique de Louvain, Brussels, Belgium http://www.em-dat.net/.

Omumbo, J.A., Hay, S.I., Guerra, C.A. and Snow, R.W., (2004). The relationship between the Plasmodium falciparum parasite ratio in childhood and climate estimates of malaria transmission in Kenya. *Malar J*, 3(1): 17.

Oreskes, N., (2004). Beyond the ivory tower. The scientific consensus on climate change. *Science*, 306(5702): 1686.

Palmer, T.N. and Ralsanen, J., (2002). Quantifying the risk of extreme seasonal precipitation events in a changing climate. *Nature*, 415(6871): 512-514.

Pan, W.H., Li, L.A. and Tsai, M.J., (1995). Temperature extremes and mortality from coronary heart disease and cerebral infarction in elderly Chinese. *Lancet*, 345: 353-355.

Parry, M., Rosenzweig, C., Iglesias, A., Fischer, G. and Livermore, M., (1999). Climate change and world food security: a new assessment. *Global Environmental Change-Human and Policy Dimensions*, 9: S51-S67.

Parry, M., Rosenzweig, C. and Livermore, M., (2005). Climate change, and risk global food supply of hunger. *Philosophical Transactions of the Royal Society B-Biological Sciences*, 360(1463): 2125-2138.

Patz, J.A., Campbell-Lendrum, D., Holloway, T. and Foley, J.A., (2005). Impact of regional climate change on human health. *Nature*, 438(7066): 310-7.

Phifer, J.F., (1990). Psychological distress and somatic symptoms after natural disaster: differential vulnerability among older adults. *Psychol Aging*, 5(3): 412-20.

Pielke, R.A., (1999). Nine fallacies of floods. *Climatic Change*, 42(2): 413-438.

Prüss-Üstün, A., Mathers, C., Corvalán, C. and Woodward, A., (2003). *Introduction and Methods: assessing the environmental burden of disease at national and local levels.*, Geneva.

Randolph, S.E., Green, R.M., Peacey, M.F. and Rogers, D.J., (2000). Seasonal synchrony: the key to tick-borne encephalitis foci identified by satellite data. *Parasitology*, 121: 15-23.

Reiter, P., (2001). Climate change and mosquito-borne disease. *Environmental Health Perspectives*, 109(141-161).

Reiter, P. et al., (2004). Global warming and malaria: a call for accuracy. *Lancet Infect Dis*, 4(6): 323-4.

Roche, P., Spencer, J. and al., e., (2001). Australia's notifiable disease status, 1999. Annual report of the National Notifiable Diseases Surveillance System. *Communicable Disease Intelligence*, 25(190-244).

Rogers, D.J. and Randolph, S.E., (2000). The global spread of malaria in a future, warmer world. *Science*, 289(5485): 1763-1766.

Rogers, D.J., Randolph, S.E., Snow, R.W. and Hay, S.I., (2002). Satellite imagery in the study and forecast of malaria. *Nature*, 415(6872): 710-715.

Schanning, J., Finsen, H., Lereim, I. and Saeterhaug, A., (1986). Effects of cold air inhalation combined with prolonged submaximal exercise on airway function in healthy young males. *European Journal of Respiratory Diseases*, 68(Suppl. 143): 74-77.

Schlesinger, M.E. and Williams, L.J., (1997). *COSMIC (COuntry Specific Model for Intertemporal Climate)* http://crga.atmos.uiuc.edu/COSMIC/.

Semenza, J.C. et al., (1996). Heat-related deaths during the July 1995 heat wave in Chicago. *New England Journal of Medicine*, 335(2): 84-90.

Singh, R.B. et al., (2001). The influence of climate variation and change on diarrheal disease in the Pacific Islands. *Environ Health Perspect*, 109(2): 155-9.

Small, J., Goetz, S.J. and Hay, S.I., (2003). Climatic suitability for malaria transmission in Africa, 1911-1995. *Proc Natl Acad Sci U S A*, 100(26): 15341-5.

Stott, P.A., Stone, D.A. and Allen, M.R., (2004). Human contribution to the European heatwave of 2003. *Nature*, 432(7017): 610-4.

Sutherst, R.W., (1998). Implications of global change and climate variability for vectorborne diseases: generic approaches to impact assessments. *International Journal For Parasitology*, 28(6): 935-945.

Sutherst, R.W., Maywald, G.F. and al., e., (2004). *CLIMEX: CD and User's Guide*. Hearne Scientific Software Pty Ltd, Melbourne.

Tanser, F.C., Sharp, B. and le Sueur, D., (2003). Potential effect of climate change on malaria transmission in Africa. *Lancet*, 362(9398): 1792-8.

Tauxe, R.V. and Cohen, M.L., 1995. *Epidemiology of diarrheal diseases in developed countries*. In: M.J. Blaser, P.D. Smith, J.I. Ravdin, H.B. Greenberg and R.I. Guerrent (Editors), Infections of the gastrointestinal tract. Raven Press, New York, pp. 37-51.

Thomas, C.J., Davies, G. and Dunn, C.E., (2004). Mixed picture for changes in stable malaria distribution with future climate in Africa. *Trends Parasitol*, 20(5): 216-20.

UN-DMTP, (1990). *UN-DMTP Training Modules*, UN-DMTP.

Walther, G.R. et al., (2002). Ecological responses to recent climate change. *Nature*, 416(6879): 389-395.

WHO, (1992). *Psychological consequences of disasters*. WHO/MNH/PSF 91.3 Rev 1, World Health Organization, Geneva, Switzerland.

WHO, (2002). *The World Health Report 2002*. WHO, Geneva.

WHO, (2004a). *Heatwaves: risks and responses*. World Health Organization, Geneva.

WHO, (2004b). *The World Health Report 2004*. WHO, Geneva.

WHO, (2005). *Using climate to predict infectious disease epidemics*, WHO, Geneva.

WHO, (2006a). *Burden of disease statistics*. WHO, Geneva www.who.int/whosis/en/.

WHO, (2006b). *Climate Change and Health*. World Health Organization http://www.who.int/globalchange/climate/en/.

WHO/PTC, (1995). *Drought: Preparedness & Response in the Health Sector*, WHO/PTC.

Wigley, T.M.L., (2003). *MAGICC/SCENGEN 4.1: Technical Manual*, National Center for Atmospheric Research, Colorado, USA.

Wilkinson, P., Campbell-Lendrum, D.H. and Bartlett, C.L., 2003. *Monitoring the health effects of climate change*. In: A. McMichael et al. (Editors), Climate Change and Human Health: Risks and Responses. World Health Organization, Geneva, pp. 322.

Yohe, G. and Tol, R.S.J., (2002). Indicators for Social and Economic Coping Capacity - Moving Toward a Working Definition of Adaptive Capacity. *Global Environmental Change*, 12: 25-40.